Combinatorial Clustering Engineering in Communications: Preliminary Survey.

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The article addresses applications of combinatorial clustering engineering approach in communication networks including design of layered network architecture, routing, management. First, basic types of combinatorial clustering problems and schemes are pointed out (e.g., graph partitioning, graph clustering, clique partitioning, capacitated clustering, cluster editing, hierarchical clustering, balanced clustering, multiattribute clustering, consensus clustering, dynamic clustering). Simplified descriptions of the combinatorial clustering engineering approaches are presented (as a special ABC material). Second, clustering schemes for communications systems are described (e.g., scheme for backbone optimization, scheme for data aggregation, energy efficient schemes). Third, the literature surveys on clustering in wireless networks and mobile networks with mobile objects (e.g., in WSNs, in MANETs, in VANETs) are presented. Fourth, network clustering applications are described (e.g., network cluster formation, network design, network management, network balancing). Numerical examples illustrate the material. The material will be useful for researchers, for design engineers, and in IT/CS/engineering education.

Keywords: clustering, combinatorial clustering, combinatorial optimization, combinatorial engineering, communications, networks, heuristics, applications

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Contents

1. Introduction

1.1. Preliminaries

Clustering problems play a central role in communication networks (design, control/management, maintenance, configuration/reconfiguration). This survey is focused on applications of combinatorial clustering engineering approach for communications. In general, a simplified description of the combinatorial clustering engineering approaches is presented (as a special ABC material). A scheme of the survey is shown in Fig. 1.1. The systematization of the paper material is based on a conceptual framework of the research that is depicted in Fig. 1.2.

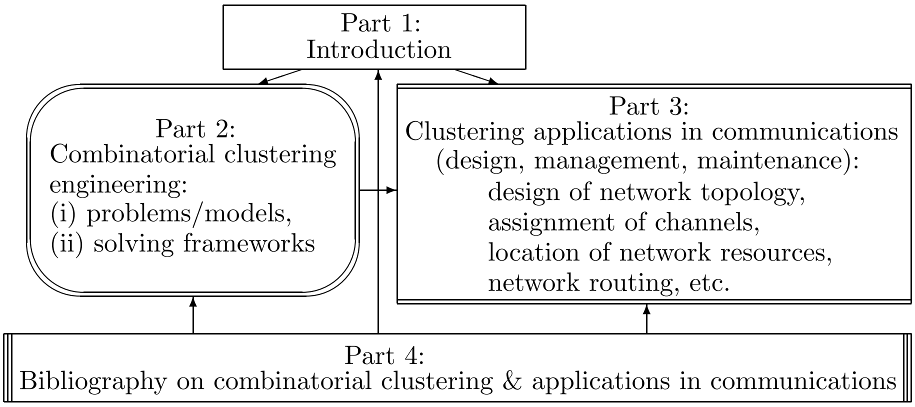


Fig. 1.1. Scheme of the survey

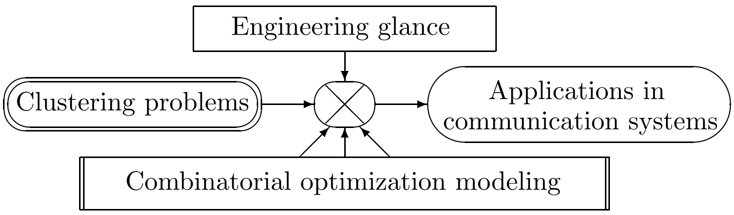


Fig. 1.2. Conceptual framework of the research

Some basic surveys on the use of clustering in communication networking and special clustering studies in the domain are listed in Table 1.1.

Clearly, the clustered networks are very useful structures for majority of problems in networking (e.g., network topology design, routing, network resource location, network covering, scheduling in networks) (e.g., [20,45,130,471,610,733,802,970,1146,1159,1175,1251,1360,1405]).

Some studies on clustered networks are listed in Table 1.2.

Some descriptions of basic types of our combinatorial clustering problems, corresponding solving approaches and some applied examples are contained in [766,769–772,777–784]. The combinatorial clustering approach is based on special composite solving framework (e.g., balanced clustering, dynamic clustering, trajectory clustering, clustering with structure over clusters, clustering with multi-type clusters) which are based on combinatorial optimization problems/models (e.g., hierarchical clustering, assignment/location, clique, graph partitioning, cluster editing, k-edge colored clustering, k-partite clustering).

A four-layer architecture for the combinatorial combinatorial clustering approach is depicted (Fig. 1.3):

Layer 1. Network applications as design of network topology, routing, control/management of networks, network maintenance (e.g., WSNs, MANETs, VANETs, HetNets, multi-hop networks).

Layer 2. Basic clustering schemes for communication networks

Layer 3. Systems combinatorial clustering frameworks (an analogue for combinatorial engineering frameworks from [767]).

Layer 4. Basic combinatorial clustering optimization models/problems or procedures (e.g., [347,482, 623–625,766,769,771,1293]).

Table 1.1. Surveys on clustering in communication networking and some specials studies

No.	Survey/overview	Source(s)
1.	Basic survey studies:	
1.1.	Survey on clustering algorithms for wireless sensor networks	[6]
1.2.	Node clustering in WSNs (recent developments & deployment challenges)	[1344]
1.3.	Literature survey on clustering in sensor networks (typical clustered networks, objective for clustering, classification of methods)	[20]
1.4.	Comparative survey of VANETs clustering techniques	[345]
1.5.	Review of moving object trajectory clustering algorithms	[1356]
1.6.	Survey on clustering in heterogeneous and homogeneous wireless sensor networks	[1080]
1.7.	Optimized clustering algorithms for large wireless sensor networks (review)	[1094]
1.8.	Survey on clustering techniques for cooperative wireless networks	[1194]
1.9.	Survey of clustering algorithms for cognitive radio ad hoc networks	[976]
1.10.	Survey and taxonomy of clustering algorithms in 5G	[682]
1.11.	Review on semi-supervised clustering	[267]
1.12.	Clustering objectives in WSNs (survey and research direction analysis)	[1125]
1.13.	Clustering in WSNs (classical methods, optimization, machine learning)	[94]
2.	Survey on clustering routing protocols:	
2.1.	Survey on clustering routing protocols in wireless sensor networks	[832]
2.2.	Typical hierarchical routing protocols for wireless sensor networks (review)	[833]
2.3.	Survey of energy-efficient clustering routing protocols for WSNs (metaheuristics)	[378]
3.	Studies of special topics:	
3.1.	Survey on unequal clustering protocols in WSNs	[120]
3.2.	Multi-criterion optimization for energy efficient cluster formation in WSNs	[128]
3.3.	Trajectory data mining (overview)	[1401]
3.4.	Survey on trajectory clustering analysis	[203]
3.5.	Cluster-based data fusion to analyze big data (wireless multi-sensor systems)	[399]
3.6.	Comparison of clustering heuristics for scheduling directed acyclic graphs onto multiprocessors	[489]
3.7.	Multi-layer network clustering in smart multi-floor building	[269]
3.8.	Multi-field packet classification (e.g., in modern software-defined data center networks)	[801,1060,1210]
3.9.	Distributed satellite cluster network (spectrum-power tradeoff, optimization)	[1285]
3.10.	Fuzzy-clustering based approach for MADM handover in 5G ultra-dense networks	[843]

Table 1.2. Some studies on clustered communication networks

No.	Study	Source(s)
1.	Some typical clustered communication networks:	
1.1.	Clustered sensor networks	[20,802]
1.2.	Clustered wireless ad-hoc networks	[45]
1.3.	Clustered wireless sensor networks	[610,733,1251,1360]
1.4.	Clustered heterogeneous wireless sensor networks	[130,1175,1405]
1.5.	Self-organizing and resource efficient clustered blockchain network	[405]
2.	Problems on clustered networks:	
2.1.	Routing based on clustered networks	[130,1360]
2.2.	Resource allocation in clustered networks	[694]
2.3.	Coverage problems for clustered wireless sensor networks	[1146,1159]
2.4.	Scheduling in clustered networks and clustering-based scheduling	[608,1117,1322,1372]
2.5.	Communication protocol design for clustered networks	[1175,1405]
2.5.	Hierarchical topology design based on clustered networks	[1257]
2.6.	Dynamics of the clustered wireless sensor network	[471]
2.7.	Slot allocation protocol for multi-cluster sensor networks	[1299]
2.8.	Examination of cluster topology in WSN	[1098]

In general, a cluster (i.e., an element group) is examined as a set of very close (similar) items (vertex/node in a graph/network). Note clique structures (i.e., a complete subgraph) are examined as a basic cluster structures. In recent decades, some generalizations (modifications) of clique (as "near cliques") are under consideration for clustering applied problems: (1) quasi-cliques [995,1095], (2) k-clique [273,852], (3) top-k maximal quasi-clique [1095], (4) massive quasi-clique (e.g., α-quasi-clique)

[12], (5) dense k-subgraph [451,503], (6) pseudo clique [557], (7) k-clubs structure [155,230,852,911,1252], (8) k-plex structures, i.e., k-plexes (e.g., maximum k-plex) [154,155,343,588,882], (9) k-defective cliques [290,323], (10) $k-CT$ components [1027], and (11) k-partite cliques in k-partite graphs (or morphological cliques) [763,767,1015].

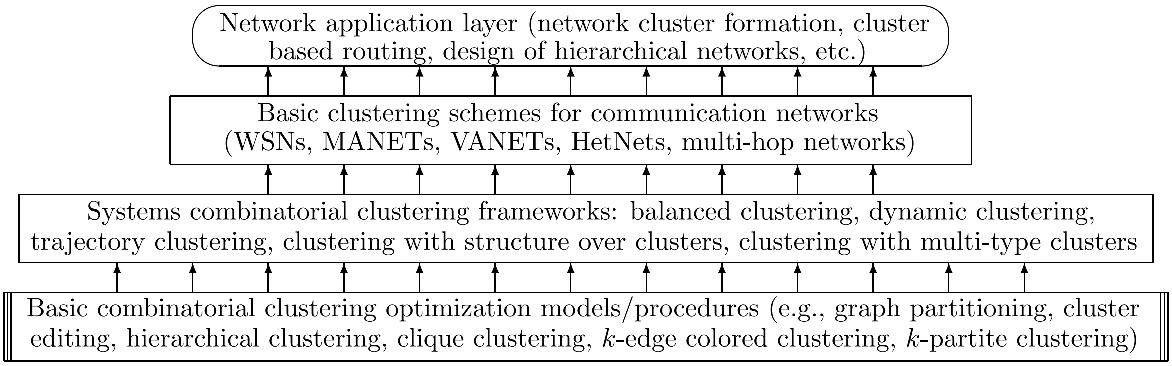


Fig. 1.3. Four-layer architecture

1.2. Classification of clustering schemes in communication networks

Table 1.3 contains a list of basic surveys on clustering schemes/algorithms for communications networks.

Table 1.3. Surveys of clustering schemes/algorithms for communications networks (taxonomies)

No.	Some studies of control issues in networks	Source(s)
1.	Surveys on clustering algorithms for wireless sensor networks (WSNs)	[6,376]
2.	Literature survey on clustering in sensor networks	[20]
3.	Surveys on clustering schemes in mobile Ad Hoc networks (MANETs)	[192,1345]
4.	Survey of clustering techniques for mobile ad hoc networks (MANETs)	[348]
5.	Comparative study of various clustering algorithms for MANETs	[997]
5.	Survey on clustering algorithms for heterogeneous wireless sensor networks	[670]
6.	Stable energy-efficient location based clustering scheme for ad hoc networks	[910]

Fig. 1.4. illustrates combination of clustering problem and some combinatorial optimization problems for generation of composite applied network design frameworks. An illustration scheme for usage of combinatorial clustering approaches (problems) in communications is depicted in Fig. 1.5.

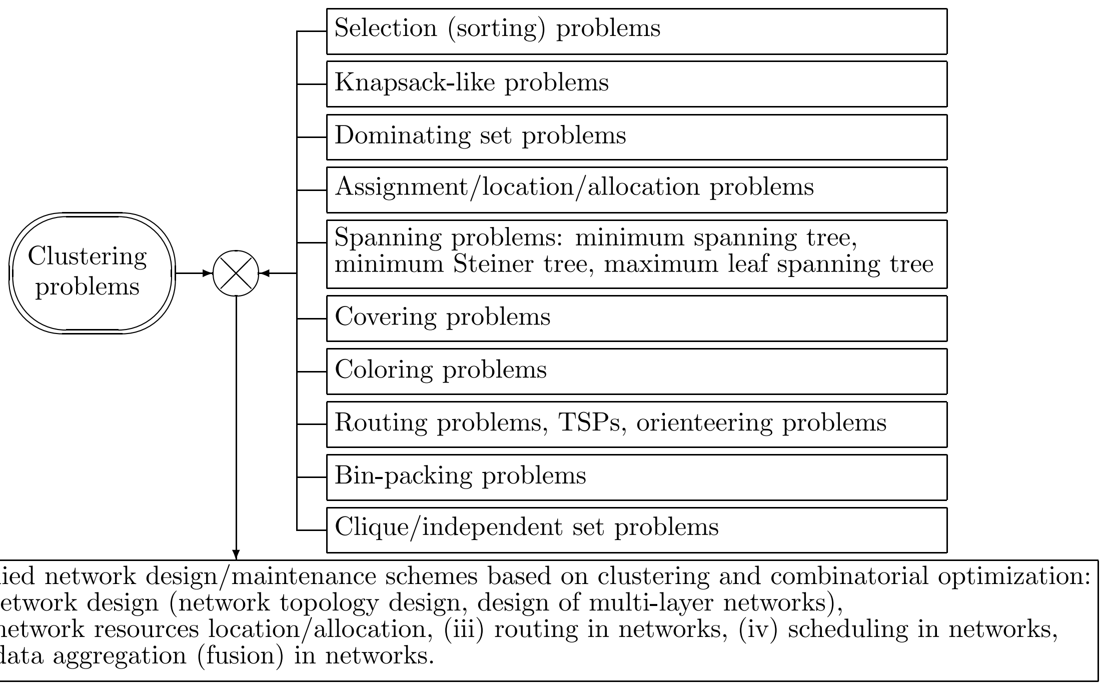


Fig. 1.4. Composite applied network design frameworks

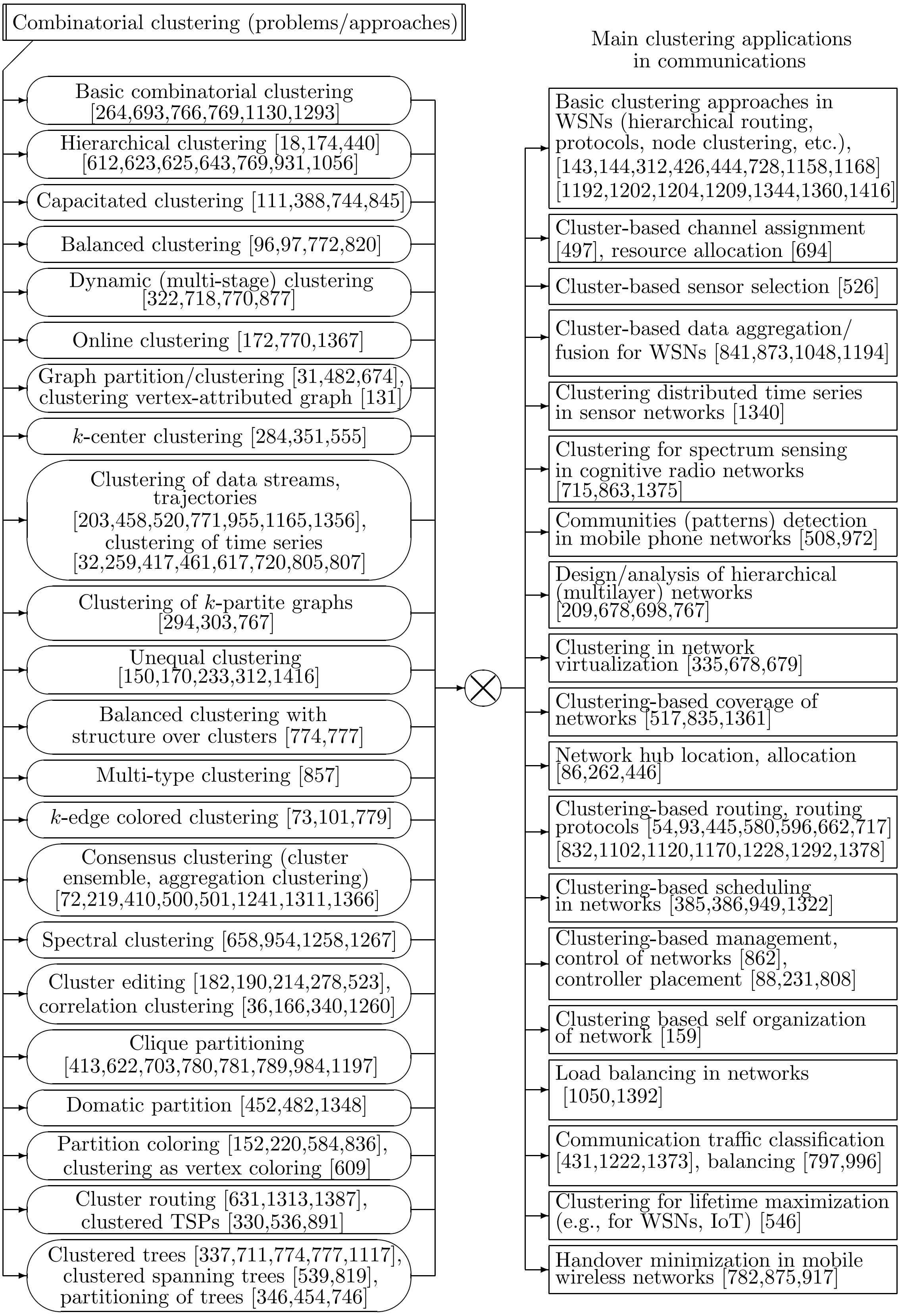


Fig. 1.5. Illustration scheme: combinatorial clustering problems in communication systems

1.3. Brief literature survey

Some basic applications of clustering approaches in communication networks are pointed in Table 1.4 (a simplified taxonomy).

Table 1.4. Basic applications of clustering in networking, Part 1

No.	Application	Source(s)
1.	Basic clustering network applications and surveys:	
1.1.	Partitioning a given network into sub-networks (location-area partition)	[137,272,1211]
1.2.	Clustering algorithms for WSNs, big data WSNs	[6,1281]
1.3.	Clustering in sensor networks	[20,827]
1.4.	Node clustering in WSNs (basic combinatorial optimization problems)	[1344]
1.5.	Routing protocols in WSNs (survey)	[54]
1.6.	Survey on balanced clustering (problems, methods, applications)	[771]
1.7.	Survey on clustering routing protocols in WSNs	[832]
1.8.	Hierarchical routing protocols for WSNs	[833]
1.9.	Comparison of clustering routing algorithms in networks (LEACH, HEED, DWENC, PEGASIS, CCS, S-WEB, BEE(M), Smart-BEEM)	[1318]
1.10.	Clustering-based routing protocols in WSNs (survey)	[54]
1.11.	Cluster-based routing protocols for WSNs	[1148]
1.12.	Design guidelines for WSNs: communication, clustering and aggregation	[894]
1.13.	Survey of energy-efficient hierarchical cluster-based routing in WSNs	[1168]
1.14.	Graph partitioning in mobile networks (tariff zones)	[204]
1.15.	GACO - metaheuristic for the dynamic load-balanced clustering in ad hoc networks	[579]
1.16.	Clustering distributed time series in sensor networks	[1340]
1.17.	Energy efficient topology management scheme based on clustering techniques for software defined wireless sensor network (SD-WSN)	[398]
1.18.	Survey on clustering techniques in VANETs (improvement of routing scalability and reliability in VANETs)	[345]
1.19.	Ranking-based clustering of heterogeneous information networks with star network schema	[1198]
1.20.	Clustering concept in cellular systems (using D2D communication)	[713]
1.21.	Cluster-centric small cell networks	[317]
1.22.	Clustering in VANET (to reduce data loss in mobile cloud computing)	[124]
1.23.	An Energy Efficient Load–Based Clustering Method for Mobile WSNs (survey)	[65]
1.24.	Clustering in heterogeneous and homogeneous WSNs (survey)	[1080]
1.25.	Clustering techniques for cooperative wireless networks	[1194]
1.26.	Optimal energy aware clustering in sensor networks	[493]
1.27.	Service clustering (for cloud-based IoT, web systems)	[28,986]
2.	Design of hierarchical (multi-level) network:	
2.1.	Hierarchical agglomerative clustering in WSNs	[854]
2.2.	Three-layer low-energy adaptive clustering hierarchy for WSNs	[756]
2.3.	Multi-layer architecture for WSNs	[678,679]
2.4.	EEMC: An energy-efficient multilevel clustering algorithm for large-scale WSNs	[641]
2.5.	Network modularization problems (network clustering, network modularity optimization)	[149]
2.6.	Design of three-layer network architecture (mobile collector, cluster head layer, sensor clusters)	[1392]
2.7.	Clique-based hierarchical clustering for dense sensor network	[216]
2.8.	Clustering-based design of k-connected muli-layer network	[765,767]
2.9.	Fuzzy logic-based clustering for WSN	[946,947]
2.10.	Energy efficient clustering algorithm for multi-hop WSN (using type-2 fuzzy logic)	[947]
2.11.	Distributed multi-criteria clustering for communication networks	[226,949]
2.12.	Multi-criterion optimization techniques for energy efficient cluster formation (WSNs)	[128]
2.13.	Distributed energy-efficient clustering for heterogeneous WSNs	[1039]
2.14.	EEHC: energy-efficient heterogeneous clustered scheme for WSNs	[395]
2.15.	Heuristic self configuration model for WSNs (hierarchy of clusters)	[610]
2.16.	COCA: constructing optimal clustering architecture (max sensor network lifetime)	[794]
2.17.	Network clustering via clique relaxation (community based approach)	[1253]
2.18.	Clustering based prize-collecting network design on planar graphs	[185]
2.19.	Low energy adaptive clustering hierarchy (with deterministic cluster-head selection)	[552]

Table 1.4. Basic applications of clustering/grouping in networking, Part 2

No.	Application	Source(s)
3.	Cluster head (CH) election/selection/assignment:	
3.1.	Cluster head selection in ubiquitous sensor networks, WSNs	[61,1183]
3.2.	Distance based thresholds for cluster head selection in WSNs	[657]
3.3.	Cluster head election for energy and delay constraint applications of WSNs	[1213]
3.4.	CHEF: cluster head election mechanism using fuzzy logic in WSNs	[688]
3.5.	Energy-efficient cluster head selection in cluster routing for WSNs	[589]
3.6.	Dynamic cluster head selection method for WSNs	[637]
3.7.	Threshold-based cluster head replacement in WSNs	[363]
3.8.	Double-phase cluster-head election (distributed energy-efficient clustering protocol for WSNs)	[549]
3.9.	Choice the best CH from the alternatives in WSNs (multicriteria approaches: TOPSIS, AHP, PROMETHEE)	[142,548,1050]
3.10.	Cluster head selection technique for edge-computing based Internet of Medical Things (IoMT) systems	[550]
3.11.	Cluster heads selection and assignment of nodes to cluster-heads in cluster-based Ad Hoc networks	[329]
3.12.	Clusterhead node placement approaches for hierarchical heterogeneous sensor networks	[988]
3.13.	Logical structure based fault tolerant approach to handle leader election in mobile ad hoc networks	[1144]
3.14.	Cluster head selection for cooperative sensor network	[201]
3.15.	Dynamic cluster head selection for WSN	[637]
4.	Clustering-based routing:	
4.1.	Clustering routing protocol for wireless networks	[570]
4.2.	Cluster oriented agent based routing protocol for MANET	[1163]
4.3.	Cluster based routing schemes for WSNs	[93,1082]
4.4.	Cluster based routing protocol for mobile nodes in WSN	[107]
4.5.	Clustering routing scheme in Ad Hoc WSNs (dominating set based algorithm)	[1297]
4.6.	Adaptive clustering approach based on minimum travel route planning for WSNs with a mobile sink	[1204]
4.7.	Multi-hop data communication algorithm for clustered WSNs	[733]
4.8.	Smart multihop clustering routing algorithm (Smart-BEEM) for MIMO IoT systems	[1318]
4.9.	Dynamic hierarchical protocol based on combinatorial optimization (DHCO) for WSNs	[289]
4.10.	Unequal cluster based routing protocol in WSNs	[312,1416]
4.11.	Evolutionary based routing protocol for clustered heterogeneous WSNs	[130]
4.12.	Clustering-based routing protocols in WSNs (survey)	[54]
4.13.	Energy-efficient cluster head selection in cluster routing for WSNs	[589]
4.14.	Secure cluster-based multipath routing protocol for WMSNs	[81]
4.15.	Hierarchical cluster-based routing in WSNs	[601]
4.16.	Intelligent hierarchical cluster-based routing	[878]
4.17.	Energy-efficient chain-cluster based intelligent routing technique for WSNs	[1053]
4.18.	Two-echelon multiple-vehicle locationrouting problem with time windows for optimization of sustainable supply chain network	[511]
4.19.	Partitioning-hub location-routing problem in networks	[272]
4.20.	Intra cluster routing techniques (WSNs)	[628]
4.21.	Delay-constrained energy-efficient cluster-based multi-hop routing in WSNs	[605]
4.22.	Cluster-based energy efficient routing in WSNs	[867]
4.23.	Power efficient cluster-based routing for WSNs (honeybees swarm intelligence)	[115]
4.24.	Automatic clustering for routing in multilevel networks	[1292]
4.25.	Cluster-based approach for routing in dynamic networks	[717]
4.26.	Evidence-efficient multihop clustering routing scheme for large-scale WSNs	[796]
4.27.	Hybrid clustering-based routing protocol for VANET (k-means, maximum stable set, hopfield network)	[655]
4.28.	Traffic-aware clustering-based routing protocol for vehicular ad-hoc networks	[540]
4.29.	Fault-tolerant clustering-based multipath routing for WSNs	[918]

Table 1.4. Basic applications of clustering/grouping in networking, Part 3

No.	Application	Source(s)
5.	Clustering-based communication protocols:	
5.1.	LEACH, clustering routing protocol for wireless networks (fully distributed clustering protocol, CH selection is based on random function)	[354,570,571] [916,1178]
5.2.	HEED (multi-hop path based on the chosen CHs)	[1343]
5.3.	EHEED (extension of HEED by multi-hop intra-cluster transmissions)	[1115]
5.4.	PEACH: power-efficient and adaptive clustering hierarchy protocol for WSNs	[1338]
5.5.	DHCR: energy-aware clustering protocol	[1084]
5.6.	EDIT: low cost clustering protocol	[1213]
5.7.	SEECH: Scalable energy efficient clustering hierarchy protocol in WSNs	[1209]
5.8.	Distributed energy-efficient clustering protocol for WSNs	[280]
5.9.	Geocasting protocols for mobile ad hoc networks based on hybrid clustering	[701]
5.10.	Cluster based routing protocol for mobile nodes in WSN	[107]
5.11.	Energy-aware distributed clustering protocol in WSNs using fuzzy logic	[1202]
5.13.	Efficient clustering protocol for WSNs based on localized game theoretical approach	[1314]
5.14.	Stable selection and reliable transmission protocol for clustered heterogeneous WSNs	[1405]
5.15.	Energy-efficient self-organized clustering for WSNs (EECSM - proposed clustering-based routing protocol)	[755]
5.16.	Hybrid cluster-based target tracking protocol for WSNs	[1269]
5.17.	Cluster-based routing protocol ACT (arranging cluster sizes and transmission ranges for WSNs)	[741]
5.18.	Biologically-inspired clustering protocol for WSNs	[1114]
5.19.	SEP: a stable election protocol for clustered wireless HetNets	[1175]
5.20.	HEEP (hybrid energy-efficient protocol) based on chain clustering	[228]
5.21.	Threshold-based cluster head replacement protocol for WSNs	[363]
5.22.	Unequal clustering protocols in WSNs (survey)	[120]
5.23.	Balanced power-aware clustering and routing protocol for WSNs	[364]
5.24.	DCE: distributed energy-efficient clustering protocol for WSNs (based on double-phase cluster-head election)	[549]
5.25.	ECDC: An energy and coverage-aware distributed clustering protocol for WSNs	[517]
5.26.	AEA-FCP: an adaptive energy-aware fixed clustering protocol for data dissemination in wireless sensor networks	[365]
5.27.	Hierarchical virtual backbone construction protocol for mobile ad hoc networks	[1143]
6.	Clustering-based scheduling in networks:	
6.1.	Hierarchical clustering-task scheduling policy in cluster-based WSNs	[949]
6.2.	Scheduling sleeping nodes in high density cluster-based sensor networks	[385]
6.3.	Balanced-energy sleep scheduling scheme for high-density cluster-based sensor networks	[386]
6.4.	Hierarchical clustering-task scheduling policy in cluster-based WSNs	[1013]
6.5.	Scheduling tasks with small communication delays for clusters of processors	[156]
7.	Clustering methods for spectrum sensing in cognitive networks:	
7.1.	Clustering methods for distributed spectrum sensing in cognitive radio systems	[863]
7.2.	Cluster-based adaptive multi spectrum sensing and access in cognitive radio networks	[1375]
7.3.	Energy efficient clustering approach for cooperative spectrum sensing in cognitive radio networks	[715]
7.4.	Energy-efficient spectrum aware clustering for cognitive radio sensor networks	[1374]
7.5.	Sensing-throughput tradeoff in cluster-based cooperative cognitive radio networks	[480]

Table 1.4. Basic applications of clustering/grouping in networking, Part 4

No.	Application	Source(s)
8.	Security in cluster-based networks:	
8.1.	Securing cluster-based ad hoc networks with distributed a9uthorities	[790]
8.2.	Provably secure hybrid key agreement protocols in cluster-based	[419]
8.3.	Anonymous cluster-based MANETs with threshold signature	[993]
8.4.	Secure cluster-based multipath routing protocol for WSNs	[81,732]
8.5.	Unequal secure cluster-based distributed routing protocol for WSNs	[1256]
8.6.	Security of clustered sensor networks	[970]
8.7.	Lightweight security scheme for query processing in clustered WSNs	[494]
9.	Cluster-based channel planning (resource allocation, slot allocation), clustering in multiple access transmission technologies:	
9.1.	Distributed delay-balancing slot allocation algorithm for 802.11s mesh coordinated channel access	[761]
9.2.	Dynamic user clustering and power allocation for uplink and downlink non-orthogonal multiple access (NOMA) systems	[75]
9.3.	Performance analysis of reuse-partitioning-based subchannelized OFDMA uplink systems in multicell environments	[967]
9.4.	Clustering-based interference management in densely deployment femtocell networks (OFDM-based femtocell network)	[357]
9.5.	Clustering technique for digital communication channel equalization (using radial basis function networks)	[304]
9.6.	Local search study of honeycomb clustering algorithm for cellular planning	[352]
9.7.	Efficient cluster-based CDMA/TDMA scheme for wireless mobile ad-hoc networks (a learning automata approach)	[43,45]
10.	Cluster-based control/management for networks, self organization of networks:	
10.1.	DEMAC: A cluster-based topology control for ad hoc networks	[862]
10.2.	Cluster tree based self organization of WSNs	[159]
10.3.	Dynamic power management in cluster system (Markov decision process)	[968]
10.4.	Resource management in cellular and IoT networks (clustering and data aggregation)	[604]
10.5.	Fuzzy-based approach for cluster management in VANETs	[980]
10.6.	Hierarchical distributed management clustering protocol for WSNs	[1124]
10.7.	Clustering for controller placement (e.g., in SDN)	[88,231,808]
11.	Load balancing:	
11.1.	Geographic load balancing for mobile cellular networks	[411]
11.2.	Cell load balancing in wireless networks	[692]
11.3.	Adaptive load balancing with preemption for multimedia cellular networks	[687]
11.4.	Load balanced clustering in WSNs	[1392]
11.5.	Load-balancing for QoS optimization in wireless LANs	[237]
11.6.	Optimized and load balanced clustering for WSNs (using MADM approaches)	[1050]
11.7.	Distributed load balancing unequal clustering in WSNs (fuzzy approach)	[170]
11.8.	Optimized and load balanced clustering for WSNs in increase the lifetime	[1051]
11.9.	MCBC: Multi-objective Load Balancing Clustering technique in WSNs	[1057]
12.	Main applications of balanced clustering:	
12.1.	Geographically partitioning the network into several disjoints and equally sized cellular regions	[287]
12.2.	Assignment of cluster heads	[38,1266,1393]
12.3.	Clustering-based design of k-connected network	[765,767]
12.4.	Network modularization problems (network clustering, network modularity optimization)	[149]
12.5.	Balanced clustering of network by cluster structure	[771]
12.6.	Energy-balanced clustering for gradient-based routing in WSNs	[831]
12.7.	Energy efficient routing in WSNs through balanced clustering	[959]

Table 1.4. Basic applications of clustering/grouping in networking, Part 5

No.	Application	Source(s)
13.	Clustering-based object tracking, time series clustering:	
13.1.	Real-time object tracking in sensor networks (by mining and predicting movement patterns)	[1231]
13.2.	Dynamic clustering for target tracking in WSNs	[308]
13.3.	Adaptive dynamic cluster-based protocol for target tracking in WSNs	[1325]
13.4.	Adaptive dynamic cluster-based protocol for target tracking in WSNs	[1325]
13.5.	Time series clustering via community detection in networks	[461]
13.6.	Dynamic cluster assignment for multi-target tracking in heterogeneous WSNs	[936]
14.	Clustering-based network virtualization, virtual clustering:	
14.1.	Wireless sensor network virtualization: a survey	[613,679,806]
14.2.	Network virtualization: State of the art and research challenges	[335]
14.3.	Virtualization in wireless sensor network: challenges and opportunities	[614]
14.4.	Multi-layer architecture for wireless sensor network virtualization	[678]
14.5.	Joint virtual edge-clustering and spectrum allocation scheme for uplink interference mitigation in C-RAN	[544]
15.	Dynamic clustering in networks (including mobile/dynamic networks):	
15.1.	Dynamic clustering method towards improved WSN longevity	[1355]
15.2.	Dynamic clustering and resource allocation algorithm for downlink CoMP systems with multiple antenna UEs	[168]
15.3.	Dynamic clustering in wireless networks with multi-cell cooperative processing	[991]
15.4.	Dynamic clustering for multi-user distributed antenna system	[828]
15.5.	Dynamic clustering of base stations for future wireless networks	[992]
15.6.	Dynamic joint clustering scheduling for downlink CoMP systems with limited CSI	[167]
15.7.	Dynamic user-centric clustering for uplink cooperation in multi-cell wireless networks	[1384]
15.8.	Joint scheduling and dynamic clustering in downlink cellular networks	[505]
15.9.	Partitioning and offloading in smart mobile devices for mobile cloud computing (survey)	[518]
15.10.	Weighted clustering for mobile Ad Hoc networks	[296]
15.11.	Cluster-based approach for routing in dynamic networks	[717]
15.12.	Dynamic clustering algorithm for multi-user distributed antenna system	[828]
15.13.	Energy and delay efficient dynamic cluster formation (using hybrid AGA with FACO in EAACK MANETs)	[1099]
15.14.	Dynamic clustering in cooperative communications (mobile ad hoc networks)	[1103]
15.15.	Data similarity aware dynamic node clustering (WSNs)	[496]
15.16.	Robust genetic algorithm for dynamic cluster formation in WSNs	[924]
16.	Multicriteria clustering in networks:	
16.1.	Multi-objective clustering for WSNs	[541]
16.2.	Energy-efficient clustering in mobile ad-hoc networks	[74]
16.3.	Multi-objective energy-efficient dense deployment in WSNs	[709]
16.4.	Multicriteria clusterhead selection in WSNs	[142,548,1050]
16.5.	Multi-criteria clustering in WSNs (cluster formation)	[128]
16.6.	Multiple attribute decision making for cooperative clustering in wireless body area networks (dynamic cluster head selection)	[333]
16.7.	Multi-criterion optimization for energy efficient cluster formation in WSNs	[945]
16.8.	MCBC: Multi-objective Load Balancing Clustering technique in WSNs	[1057]
16.9.	MOFCA: multi-objective fuzzy clustering algorithm for WSNs	[1116]
16.10.	Multi-objective particle swarm optimization for energy-efficient clustering in mobile ad-hoc networks	[74]

Table 1.4. Basic applications of clustering/grouping in networking, Part 6

No.	Application	Source(s)
17.	Cluster-based network coverage:	
17.1.	Coverage in WSNs (by distributed energy-efficient clustering)	[835]
17.2.	Coverage problems in wireless sensor networks (survey)	[443]
17.3.	α-Overlapping area coverage for clustered directional sensor networks	[1146]
17.4.	Clustering self organizing map protocol for existing WSN lifetime and coverage	[427]
17.5.	Inter- and intra -cluster movement of mobile sink algorithm for cluster-based networks to enhance the network lifetime	[491]
17.6.	Coverage-aware and energy-efficient protocol for the distributed WSNs (minimum spanning tree, shortest path, cluster formation, routing, load balancing)	[319]
17.7.	Coverage-time optimization for clustered WSNs (power-balancing approach)	[1159]
18.	Special clustering studies:	
18.1.	Cluster-based data aggregation in WSNs	[470,1118]
18.2.	Traffic aware balancing for mobile ad-hoc networks	[996]
18.3.	Traffic balancing in heterogeneous networks	[797]
18.4.	Network hub location	[86,262,446]
18.5.	Allocation of end-users to access points (end-user grouping - multicriteria assignment)	[766,769,785]
18.6.	Scheduling in multi-beam antenna communication system	[766,769]
18.7.	Stations/devices grouping under dynamic traffic for IEEE 802.11ah networks	[360,1217,1342]
18.8.	Cluster based iterative GPS-free localization for WSNs	[314]
18.9.	Clustering with one-time setup for reduced energy consumption and prolonged lifetime in WSNs	[1154]
18.10.	Energy-efficient prediction clustering for multilevel heterogeneous WSNs	[1009]
18.11.	Weight-based clustering decision fusion for distributed target detection in WSNs	[594]
18.12.	Spectrum sharing for clustering cognitive ad hoc networks.	[793]
18.13.	Coordinated multipoint transmission in dense cellular networks with user-centric adaptive clustering	[483]
18.14.	Energy-aware offloading clustering approach (EAOCA) in fog computing	[232]
18.15.	Clustering-based location in wireless networks	[888]
18.16.	Fixed charge multicommodity network design using p-partition facets	[26]
18.17.	Inter-cluster interference management (cell-clustering in network MIMO systems)	[915]
18.18.	Self-organizing adaptive clustering for cooperative multipoint transmission	[1291]
18.19.	Clustering for interference alignment in multiuser interference network	[315]
18.20.	Geographical multi-layered energy-efficient clustering scheme for ad hoc distributed WSNs	[1161]
18.21.	Cluster-based data aggregation for WSNs	[873,1048]
18.22.	Multi-mode clustering model for hierarchical WSNs	[591]
18.23.	Clustering for network lifetime maximization	[546]
18.24.	Link- and hop-constrained clustering for multi-hop WSNs	[316]
18.25.	Fault-local self-stabilizing clustering service for wireless ad hoc networks	[384]
18.26.	Cluster-based data fusion for big data analysis in wireless multi-sensor systems	[399]
18.27.	CFT: A cluster-based file transfer scheme for highway VANETs	[855]
18.28.	NOMA aided narrow band IoT for machine type communications with user clustering	[1121]
18.29.	Exact solution procedure for cluster hub location problem	[1259]
18.30.	Cluster maintenance in mobile Ad-hoc networks	[1264]
18.31.	Clustering in transport communications (cooperative content distribution framework for highway vehicular communications	[1407]
18.32.	Genetic algorithm for two-mode KL-means partitioning in binary/real-valued social networks	[245]
18.33.	Clustering the wireless Ad Hoc networks: distributed learning automata approach	[42]
18.34.	Mobility-driven user-centric AP clustering in mobile edge computing-based ultra-dense networks	[567]
18.35.	Approximation for multi-hop connected clustering problem in wireless networks	[477]
18.36.	Modeling and analyzing cascading dynamics of the clustered WSN	[471]
18.37.	Combinatorial clustering for communications fraud detection	[1349]
18.38.	Fast fractal clustering approach for SOAP traffic	[63]

1.4. Illustrations of clustering-based (hierarchical) communication systems

In this section some illustrative cluster-based hierarchical schemes of communication systems are presented.

A simplified illustration of basic cluster-based multi-layer hierarchical structure of communication system is depicted in Fig. 1.6 (e.g., [649]): (i) Internet, (ii) global base station, (iii) base stations, (iv) cluster heads, (v) members/nodes (end users, sensors). In addition, two gateways are depicted (to connect members of different clusters).

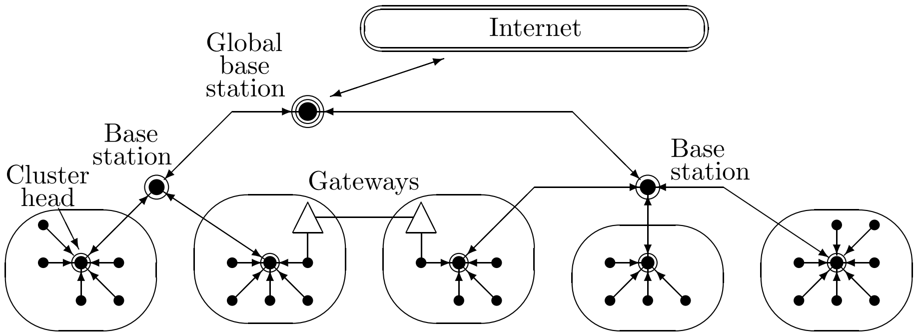


Fig. 1.6. Simplified illustration of hierarchical cluster structure

An illustration of cluster-based structure in hierarchical mobile communication network (MANET) is depicted in Fig. 1.7.

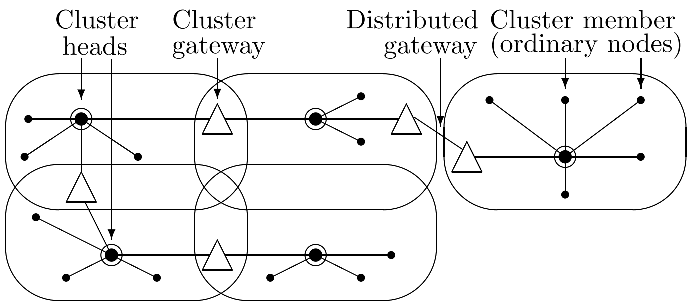


Fig. 1.7. Illustration of cluster structure in MANET

An illustrative example of multi-part Internet topology is depicted in Fig. 1.8 (e.g., [261]).

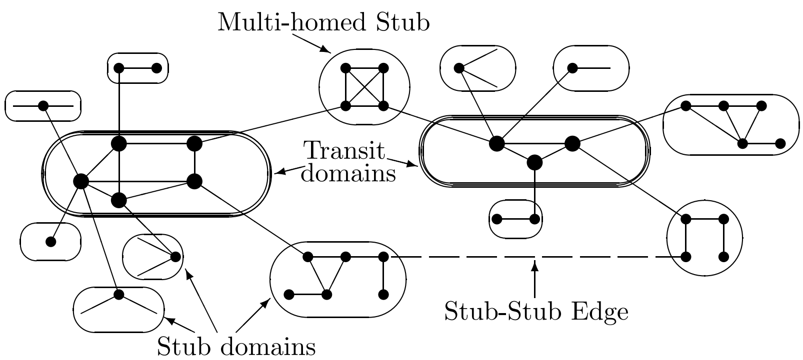


Fig. 1.8. Illustrative example of multi-part Internet topology

A hierarchical architecture of multi-layer mobile cellular network is shown in Fig. 1.9 (based on [394]):

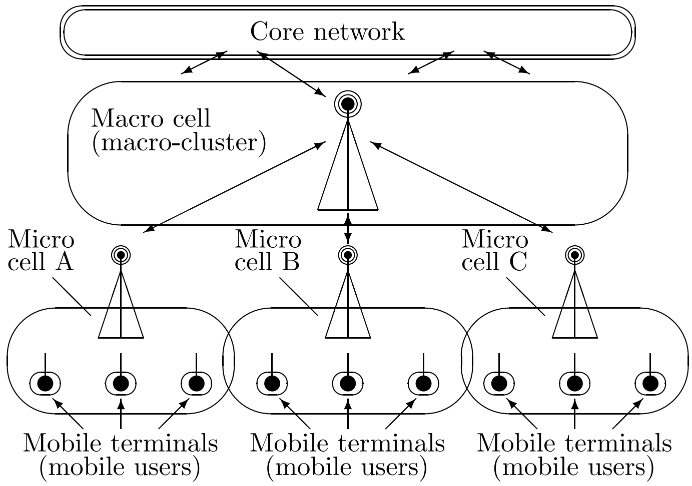


Fig. 1.9. Architecture of multi-layer mobile cellular network

An architecture scheme of hierarchical cellular Ad Hoc V2V wireless network is shown in Fig. 1.10.

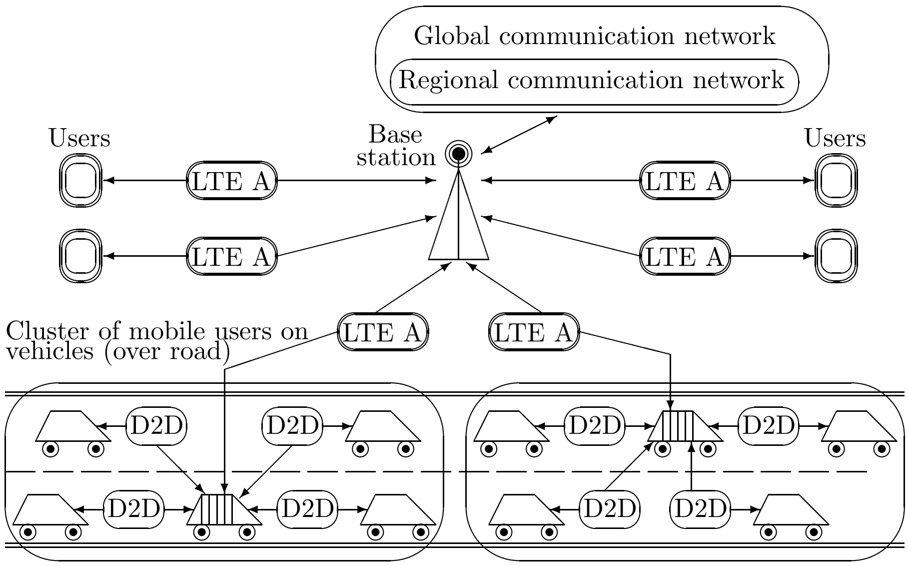


Fig. 1.10. Hierarchical cellular Ad Hoc V2V wireless network

A simplified scheme of hierarchical distributed cloud topology that is based on a set of wireless sensor networks is presented in Fig. 1.11.

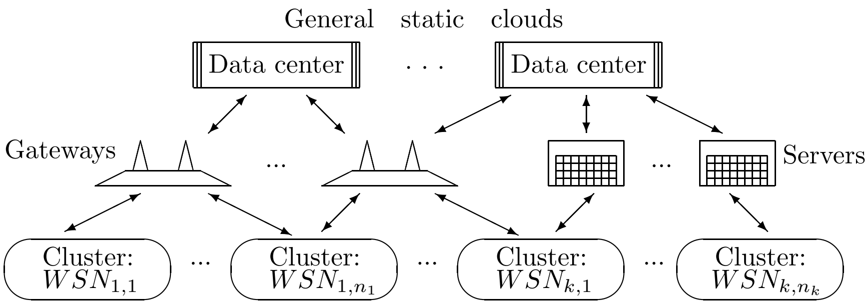


Fig. 1.11. Simplified scheme of distributed cloud topology

A scheme of hierarchical architecture for space-air-ground and space-air-ground-sea integrated next generation communication systems is shown in Fig. 1.12 (e.g., [51,324,839,859,1068,1341]):

1. Space-air network part:

1.1. Space travels. 1.2. Satellite network(s). 1.3. Airspace (aeroplane, balloons, Unmanned vehicles AUVs). 1.4. Base stations

2. Ground networks part:

2.1. Local base stations. 2.2. End-Users (Industrial IoT, Health care IoT, Personal IoT): (i) ground end-users, (ii) moving ground users.

3. Marine/underwater communications networks part:

3.1. UAVs. 3.2. Ships. 3.3. Underwater cluster heads (central sensors).

3.4. Underwater sensors. 3.5. Underwater sensors.

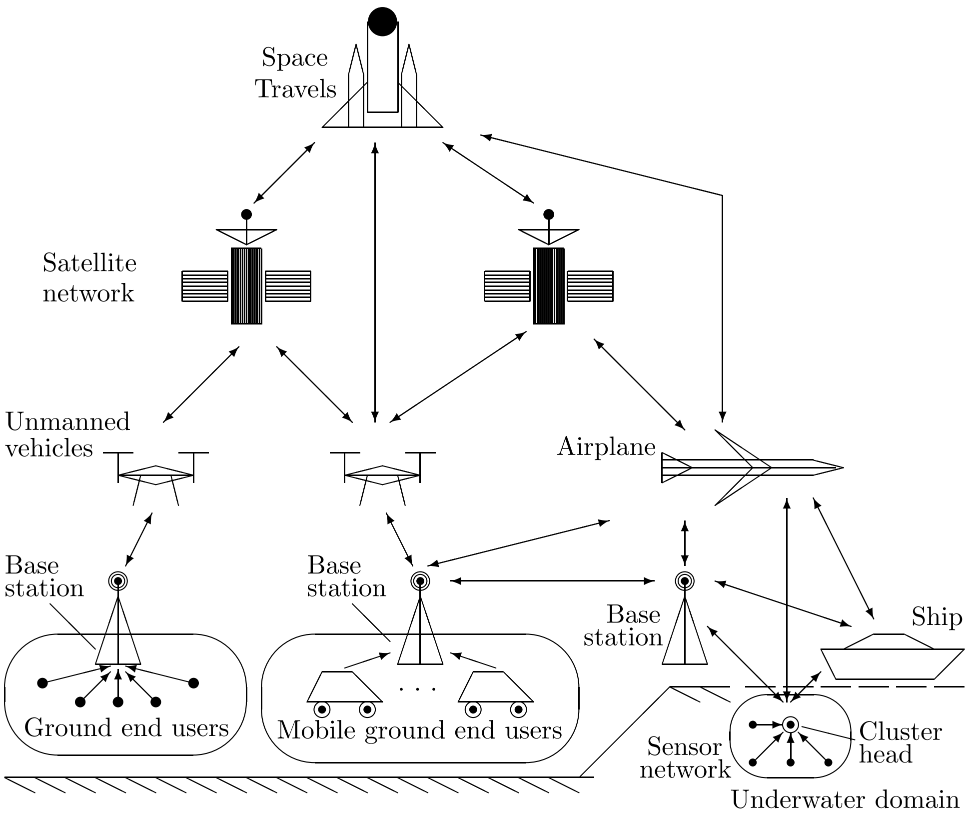


Fig. 1.12. Integrated space-air-ground-sea communication system

A general hierarchical three-layer architecture/structure of contemporary mobile/multi-access edge computing (MEC) system is depicted in Fig. 1.13 (e.g., [77,236,543,884,1254,1388]).

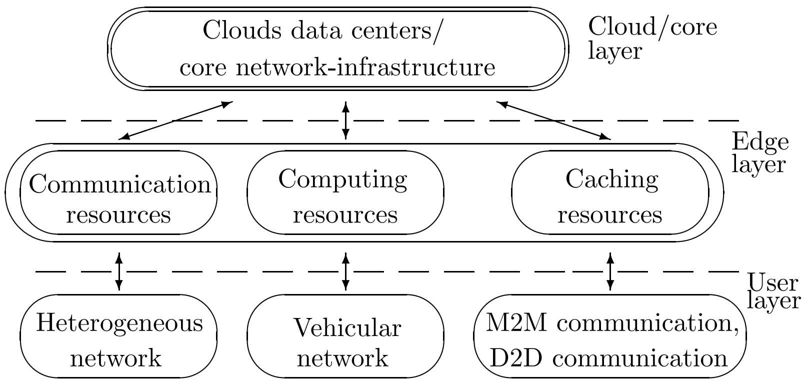


Fig. 1.13. General hierarchical MEC architecture

2. Combinatorial clustering

Here some basic combinatorial clustering problems (as combinatorial optimization problems) are described. Evidently, it is reasonable to note the following:

(1) recently a special attention is targeted to various combinatorial clustering problems, approaches and frameworks (e.g., [223,241,462,644,693,696,730,734,769,901,1130,1247]);

(2) the problems of the kinds are related and close;

(3) the special cases of the different problems of the kinds are often equivalent.

The domain of combinatorial clustering is very interesting, that involves various combinatorial optimization problems including clustering, selection, assignment, edge coloring. In general, the basic list of the combinatorial clustering problems can be extended (it is the significant topic for future studies).

2.1. Basic combinatorial clustering optimization problems

2.1.1. Graph partitioning, graph clustering

The problems of graph partitioning and graph clustering (node clustering, graph clustering) are basic problems for many theoretical and practical domains (e.g., VLSI design, processor allocation, computing planning, data mining, air traffic control, data bases, molecular biology, chemical graphs, community detection in social networks, design and management in telecommunication networks) (e.g., [31,204,482, 575,1101]). In fact, the problems are basic ones for many other types of combinatorial clustering problems and approaches (e.g., clique clustering problem, cluster deletion problem)

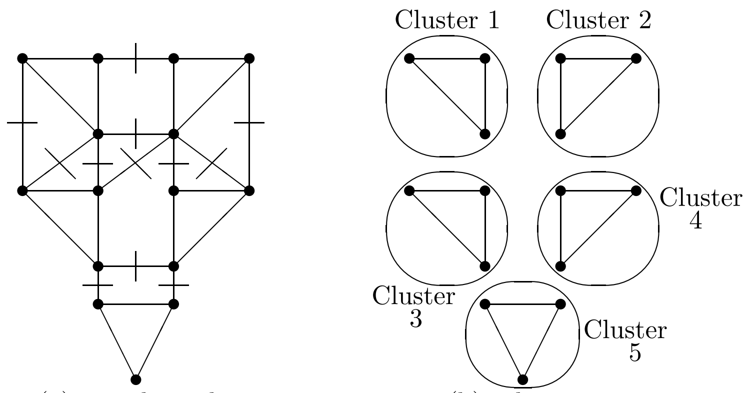
The basic graph partitioning problem is defined as follows. Given graph $G = (A, E)$ where A is the vertex set ($|A| = n$), E is the set of edges. The k graph partition problem is:

Find the partitioning of the set A into k subsets A_1,A_2,...,A_k ($k < n$) such that $|A_{i_1} \& A_{i_2}| = 0$ for $i_1 \neq i_2$ ($i_1, i_2 \in \{1, ..., k\}$) and $\bigcup_{i=1}^{k} A_i$. The number of edges of E whose incident vertices belong to different subsets is minimized.

Evidently, the subgraph of G which correspond to subsets $\{A_i | i = \overline{1,k}\}$ can be considered as clusters (i.e., graph clustering).

In the case of the weighted graph (e.g., weights of edges are used) the sum of edge-weights whose incident belong to different subsets is minimized. In addition, the sum of the vertex weight in each subset can be is considered as the same (or about the same).

An illustration example of the problem is depicted in Fig. 2.1 (5 graph partitioning, each cluster contains 3 vertices).



(a) initial graph (b) solution

Fig. 2.1. Illustration for graph partition

The problems correspond to class of NP-complete (NP-hard) problems (e.g., ([482]). Note, the graph partition problem is related to some other combinatorial optimization problems. A simplified illustration scheme of the problem relationship is depicted in Fig. 2.2.

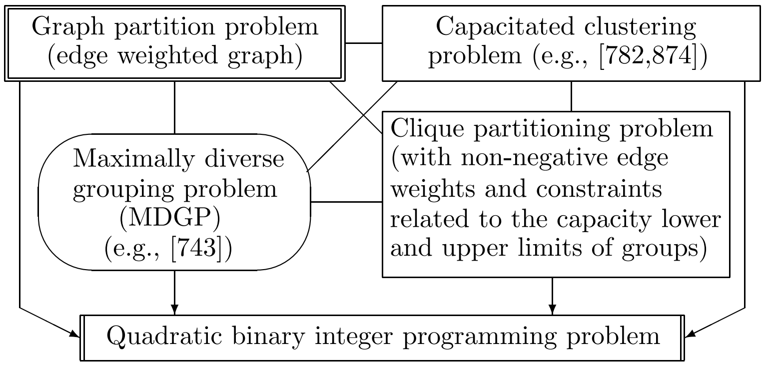


Fig. 2.2. Illustration of problem relationship

Some studies on the graph partitioning problems are listed in Table 2.1 and solving approaches are listed in Table 2.2.

Table 2.1. Some graph partitioning and graph clustering studies

No.	Study	Source(s)
1.	Surveys:	
1.1.	Graph partitioning problems (surveys)	[204,482]
1.2.	Survey of clustering algorithms for graph data	[31]
1.3.	Recent advances in graph partitioning	[253]
1.4.	Recent advances in (hyper)graph partitioning	[271]
1.5.	High quality graph partitioning (survey)	[1110]
1.6.	Review on graph clustering	[1104]
1.7.	The impact of heterogeneous multi-core clusters on graph partitioning (empirical study)	[283]
2.	Some basic problems:	
2.1.	Graph partitioning	[482,674]
2.2.	Graph partition/clustering as modularity clustering	[235]
2.3.	Graph bisection problem	[204,482]
2.4.	Clustering of vertex-attributed graphs	[131]
2.5.	Graph partitioning models (for parallel computing)	[575]
2.6.	Multi-objective graph partitioning	[1107]
2.7.	Online balanced graph re-partitioning	[1049]
2.8.	Multi-dimensional balanced graph partitioning	[134]
2.9.	Partitioning of signed graphs/networks	[113,117,408,1227]
2.10.	Model-based graph partitioning (model-based clustering of networks, modularity optimization approach)	[368]
3.	Balanced graph partitioning:	
3.1.	Balanced graph partitioning (partitioning graphs into balanced components)	[98,716,771,772]
3.2.	Advanced graph partitioning	[253]
3.3.	Balanced connected graph partition	[629]
3.4.	Balanced graph partitioning (large graphs, vertex balance, edge balance)	[424]
3.5.	Dynamic balanced graph partitioning (e.g., cloud computing)	[135]
4.	Some special graph partitioning problems:	
4.1.	Hypergraph partitioning	[271,668]
4.2.	Partitions of graphs into trees	[336,400]
4.3.	Partitioning a graph into degenerate subgraphs	[15]
4.4.	Equitable partition of graphs into induced forests	[436,962]
4.5.	Partitioning cographs into two forests and one independent set	[572]
4.6.	Partitioning cographs into p cliques and k stable sets (p,k)-coloring	[379]
4.7.	Partitioning a graph into disjoint cliques and a triangle-free graph	[14]
4.8.	Partitioning sparse graphs into an independent set and a graph with bounded size components	[331]
4.9.	k-partitioning problem, graph k-partitioning problem	[69,90,651]

Table 2.2. Some solving scheme/algorithms for graph clustering

No.	Study	Source(s)
5.1.	Efficient heuristic procedure for partitioning graphs	[674]
5.2.	Fast approximate graph partitioning algorithms	[439]
5.3.	Efficient memetic algorithm for graph partitioning problem	[475]
5.4.	Multi-way graph partitioning	[482,667]
5.5.	Parallelism in graph-partitioning	[1101]
5.6.	Multilevel scheme for partitioning irregular graphs	[666]
5.7.	Graph clustering and minimum cut trees	[465]
5.8.	Multilevel k-way hypergraph partitioning	[668]
5.9.	Prioritized restreaming algorithms for balanced graph clustering	[138]
5.10.	Effective multilevel tabu search approach for balanced graph partitioning	[191]
5.11.	Approximation algorithms for maximally balanced connected graph partitioning	[321]
5.12.	Distributed algorithm for balanced graph partitioning	[1045]
5.13.	Effective local search for enhancement of balanced graph edge partition	[528]
5.14.	K-way balanced graph partitioning (for parallel computing)	[998]
5.15.	Distributed balanced partitioning via linear embedding	[141]
5.16.	Streaming graph partitioning (online strategies, experimental study)	[4]
5.17.	Iteration vertex relocation algorithm for balanced graph partitioning (mixed 0-1 linear programming)	[1333]
5.18.	Neighborhood heuristic for graph edge partitioning	[1380]
5.19.	Parallel heuristics for balanced graph partitioning based on richness of implicit knowledge	[1330]
5.20.	Relocation heuristics, tabu search, and variable neighborhood search for partitioning signed graphs	[246]

2.1.2. Clique partitioning problem

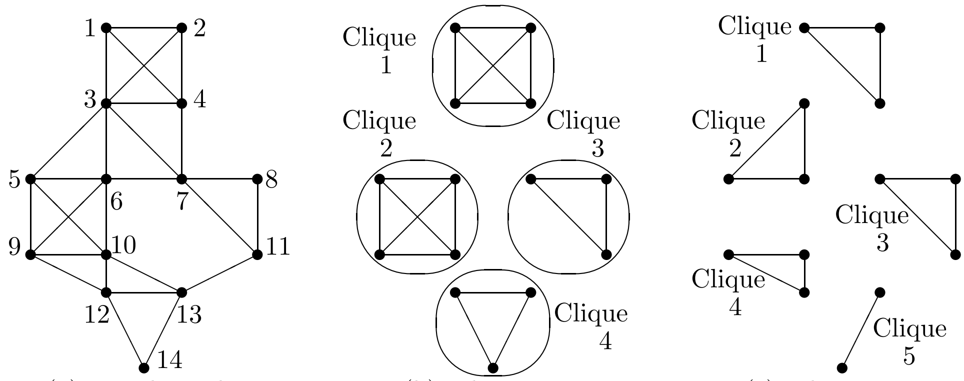
Clique partitioning problem is a special version of correlation clustering (e.g., [622,703,789,984,1197, 1408]). Here the clique partitioning problem is considered from the viewpoint of combinatorial clustering [780,781] (Table 2.3).

Table 2.3. Some recent studies on clique partitioning problems

No.	Study	Source(s)
1.	Problem formulations:	
1.1.	Clique partitioning problem	[413,622,703] [781,789]
1.2.	Maximum edge clique partitioning problem	[1030,1197]
1.3.	The clique partitioning problem in network (facets and patching facets)	[977]
1.4.	Maximum and minimum edge clique partition problems	[389]
1.5.	Edge clique partition problem for weighted graph	[293]
2.	Complexity issues:	
2.1.	Complexity of the maximum edge clique partitioning problem with respect to the clique number	[1197]
2.2.	Issues of approximability and inapproximability in edge clique partition problems	[389,1030]
3.	Solving approaches:	
3.1.	Iterated tabu search approach for the clique partitioning problem	[984]
3.2.	Noising methods for a clique partitioning problem	[293]
3.3.	Neighborhood search heuristics for the clique partitioning problem	[244]
3.4.	Solving the clique partitioning problem as a maximally diverse grouping problem	[239]
3.5.	Simulated annealing and tabu search approaches for clique partitioning	[372]
3.6.	Approximation algorithms for clique partition problems	[389]
3.7.	The 2-phase approximate greedy algorithm for the clique partitioning	[1030]
3.8.	Three-phased local search approach for the clique partitioning (heuristic, tabu search, restricted neighborhood)	[1408]
3.9.	Metaheuristics for clique partitioning problem	[1265]
3.10.	Fixed set search for clique partitioning problem	[648]
3.11.	Commercial solvers for clique partitioning problems	[413]

The description of the problem is as follows. Let $G = (A, E)$ be an initial simple undirected graph: A is the set of vertices (i.e., items, elements), E is the set of edges. Let $P = \{A_1, .., A_i, ..., A_k\}$ be a partition (disjoint subsets) of graph vertices A (i.e., $A = \bigcup_{i=1}^{k} A_i$, $|A_{i_1} \& A_{i_2}| = 0$, $\forall i_1 \neq i_2$, $i_1, i_2 \in \{1, ..., i, ..., k\}$). As a result, the following subgraph sets is obtained: $\{G_1 = (A_1, E_1), ..., \{G_i = (A_i, E_i), ..., \{G_k = (A_k, E_k)\}$. The partition P is called a clique partitioning if $G_i = (A_i, E_i)$ is a clique of G ($\forall i = \overline{1,k}$). In addition, $E^{-}(P) \subseteq E$ is called a set of edges between clusters in partitioning P.

Fig. 2.3 depicts an illustrative numerical example for clique partitioning problems with two solutions [780,781].



(a) initial graph (b) solution P_1 (c) solution P_2

Fig. 2.3. Numerical example of clique partitioning problem

The following initial undirected graph $G = (A, E)$ is considered:

(a) the set of vertices $A = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14\}$ and

(b) the set of edges $E = \{(1, 2), (1, 3), (1, 4), (2, 3), (2, 4), (3, 4), (3, 5), (3, 6), (3, 7), (4, 7), (5, 6), (5, 9), (5, 10), (6, 7), (7, 8), (7, 11), (8, 11), (9, 10), (9, 12), (10, 12), (10, 13), (11, 13), (12, 13), (12, 14), (13, 14)\}$.

Two basic clique partitioning problems are as follows (e.g., [984,1030,1197]).

Problem 1. The maximum edge clique partition problem (Max-ECP) is targeted to find a partition of the vertices into cliques such that the total number of edges within all cliques is maximized. This problem is NP-hard (for the number of the cliques ≥ 3) (e.g., [1030,1197]). The formal model of the maximum edge clique partition problem (Max-ECP) is:

Find a partition of the vertices into cliques P that maximizes the number of edges within the cliques

$$\max_{\{P\}} f_1 = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} |\{e\}|. \qquad (2.1)$$

Problem 2. The minimum edge clique partition problem (Min-ECP) is defined analogously: the total number of edges between the obtained cliques $\{G_1, ..., G_i ..., G_t\}$ is minimized:

Find a partition of the vertices into cliques P that minimizes the number of edges between the cliques

$$\min_{\{P\}} f_2 = \min_{\{P\}} \sum_{e \in E^{-}(P)} |\{e\}|. \qquad (2.2)$$

The edge partition problem for the weighted graph is examined as well (e.g., [293]). Here a nonnegative weight w_e, for each graph edge ($\forall e \in E$) is used (e.g., a proximity/difference between two items/elements). Thus the following two problems for the weighted graph can be considered:

Problem 3. Find a partition of the vertices into cliques P such that the total edge weight within all cliques is maximized. The formal model of the problem is:

Find a clique partitioning that maximizes the number of edges within the cliques

$$\max_{\{P\}} f_{w1} = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} w(e). \qquad (2.3)$$

Problem 4. The minimum weighted edge clique partition problem is defined analogously:
Find a partition of the vertices into cliques P that minimized the total weight of edges between the cliques

$$\min_{\{P\}} f_{w2} = \min_{\{P\}} \sum_{e \in E^-(P)} w(e). \qquad (2.4)$$

Further the following two-criteria edge partition problem can be formulated. The problems are:

Problem 5. Find a partition of the vertices into cliques P such that: (i) the numbers edge within all cliques is maximized and (ii) the number of edges between the cliques is minimized. The formal model of the problem:
Find a partition of the vertices into cliques P that maximizes the number of edges within the cliques and minimizes the number of edges between the cliques

$$\max_{\{P\}} f_1 = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} |\{e\}|, \quad \min_{\{P\}} f_2 = \min_{\{P\}} \sum_{e \in E^-} |\{e\}|. \qquad (2.5)$$

Problem 6. Find a partition of the vertices into cliques P such that: (i) the total edge weight within all cliques is maximized and (ii) the total edge weight between the cliques is minimized. The formal model of the problem is:

$$\max_{\{P\}} f_{w1} = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} w(e), \quad \min_{\{P\}} f_{w2} = \min_{\{P\}} \sum_{e \in E^-} w(e). \qquad (2.6)$$

Multi–criteria weighted edge partition problems can be formulated for the case when vector weight of graph edges are used: $\overline{w}(e) = (w^1(e), ..., w^j(e), ...w^t(e))$. In general, the multicriteria approach is targeted to search for Pareto-efficient solutions. The problems are:
Problem 7. Find a partition of the vertices into cliques P such that: (i) the total vector edge weight within all cliques is maximized. The formal model of the problem is:

$$\max_{\{P\}} f^1_{w1} = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} w^1(e), ..., \max_{\{P\}} f^j_{w1} = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} w^j(e), ...,$$

$$\max_{\{P\}} f^t_{w1} = \max_{\{P\}} \sum_{i=1}^{k} \sum_{e \in E_i} w^t(e). \qquad (2.7)$$

Evidently, in the simplified case it is possible to consider a summarization of the objective functions:

$$\max_{\{P\}} f^{sum}_{w1} = \max_{\{P\}} \sum_{j=1}^{t} f^j_{w1} = \max_{\{P\}} \sum_{j=1}^{t} \sum_{i=1}^{k} \sum_{e \in E_i} w^j(e). \qquad (2.8)$$

Problem 8. Find a partition of the vertices into cliques P such that: the total vector edge weight between the cliques is minimized. The formal model of the problem is:

$$\min_{\{P\}} f^1_{w2} = \min_{\{P\}} \sum_{e \in E^-} w^1(e), ..., \min_{\{P\}} f^j_{w2} = \min_{\{P\}} \sum_{e \in E^-} w^j(e), ..., \min_{\{P\}} f^t_{w2} = \min_{\{P\}} \sum_{e \in E^-} w^t(e). \qquad (2.9)$$

Evidently, in the simplified case it is possible to consider a summarization of the objective functions:

$$\min_{\{P\}} f^{sum}_{w2} = \min_{\{P\}} \sum_{j=1}^{t} f^j_{w2} = \min_{\{P\}} \sum_{j=1}^{t} \sum_{e \in E^-} w^j(e). \qquad (2.10)$$

Problem 9. Find a partition of the vertices into cliques P such that optimizes a composite vector objective function: (i) the total vector edge weight within all cliques is maximized and (ii) the total vector edge weight between the cliques is minimized. The formal model of the problem is:

$$(\max_{\{P\}} f^{sum}_{w1}, \min_{\{P\}} f^{sum}_{w2}). \qquad (2.11)$$

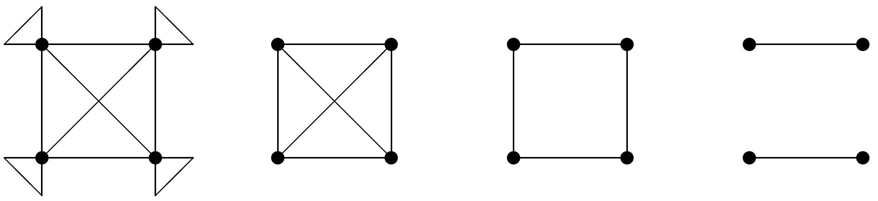
An additional approach may be based on vector ordinal estimated of the edge weights.

2.1.3. k-plex clustering

In recent decades the significance of clustering procedures which are based on quasi-clique structures has been increased. Here k-plex structure (as a version of quasi-clique, a generalization of clique) is used (e.g., [343,525,922]). The definition of k-plex in a graph $G = (A, E)$ (A is the vertex/node set, E is the edge set, $|A| = n$, $k < n$) is:

Set $\Theta \subseteq A$ of interconnected vertices (nodes) in graph $G = (A, E)$ such that $\forall \theta \in \Theta$ is linked to all the other n vertices (i.e., $\forall a \in A$), except at most k.

Some examples of k-plex structures for a 4-vertex graph are shown in Fig. 2.4. Some studies on k-plex clustering and close problems are listed in Table 2.4. The research directions in the field of k-plex problems (i.e., k-plex clustering, detection and analysis of k-plex structures, community detection based on k-plex structures) can be considered as interesting and prospective ones.



(a) 0-plex (b) 1-plex (clique) (c) 2-plex (d) 3-plex

Fig. 2.4. Examples of k-plex structures

Table 2.4. Some studies on k-plex clustering

No.	Study	Source(s)
1.	k-plex clustering and maximum k-plex problem:	
1.1.	k-plex clustering	[525,922]
1.2.	Maximum edge-weighted k-plex partitioning problem	[876]
1.3.	The maximum k-plex problem	[155,642,882,1028]
2.	Some solving approaches for the maximum k-plex problem:	
2.1.	Local search for the maximum k-plex problem	[1028]
2.2.	Effective reinforcement learning based local search for the maximum k-plex problem	[642]
2.3.	Local search algorithm with movement gap and adaptive configuration checking for the maximum weighted s-plex problem	[825]
2.4.	Combinatorial algorithms for the maximum k-plex problem	[882]
2.5.	Meta-algorithm for finding large k-plexes	[343]
2.6.	Exact combinatorial algorithms and experiments for finding maximum k-plexes	[922]
2.7.	Reduction-and-bound method for maximum k-plex search	[479]
3.	Enumeration of k-plex structures:	
3.1.	Efficient enumeration of maximal k-plexes	[198]
3.2.	Enumerating maximal k-plexes with worst-case guarantee	[1411]
3.3.	Efficient enumeration of large maximal k-plexes	[326]
3.4.	Listing maximal k-plexes in large real-world graphs	[1289]
3.5.	Parallelizing maximal clique and k-plex enumeration over graph data	[1279]
4.	Community detection based on k-plexes:	
4.1.	Community detection based on modularity and k-plexes	[1418]
4.2.	Scalable community detection in massive networks via small-diameter k-plexes	[342]

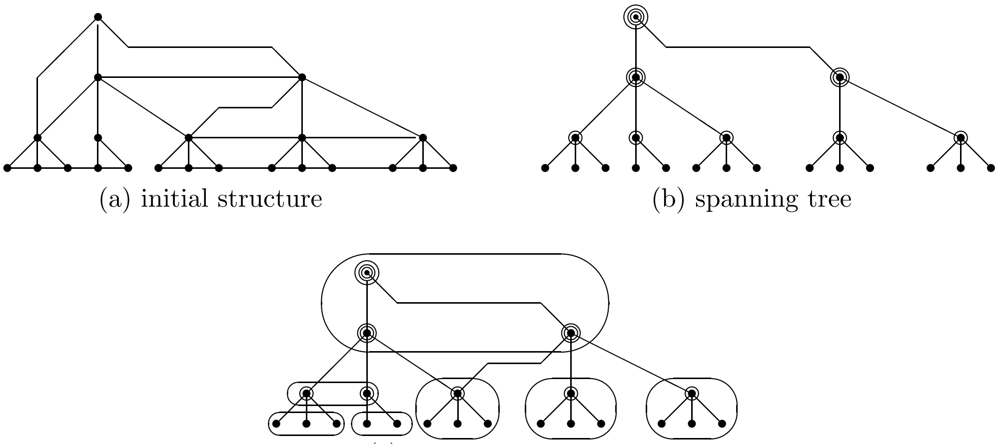
2.1.4. Spanning tree based clustering and clustered tree problems

In general, tree-like structures of data are very useful, for example: (a) the structures are very understandable, (b) the structures are a basis for the design of simple (polynomial) algorithmic approaches.

The usage of preliminary spanning tree for initial data can lead to more simple combinatorial problem (e.g., [482]). Some studies on spanning tree based clustering are pointed out in Table 2.5. Fig. 2.5 illustrates the approach: construction of a spanning tree and series detection(s) of cluster(s) (from the root node).

Table 2.5. Some recent studies on spanning tree based clustering

No.	Study	Source(s)
1.	Clustering algorithms based on minimum and maximum spanning trees	[126]
2.	Minimum spanning tree based clustering using partitional approach.	[421]
3.	Spanning tree based balanced clustering	[771,772]



(a) initial structure (b) spanning tree

(c) clustering solution

Fig. 2.5. Illustration of tree based clustering

Note, the forest-like structures can be used as well.

Table 2.6 contains a list of some studies on clustered tree problems.

An illustrative example of cluster-tree topology of WSN is depicted in Fig. 2.6 (e.g., [695,824,904]).

The complete optimal stars-clustering-tree problem is described in [711]. Here a complete graph $G = (A, E)$ with a weight on every edge (i.e., $\forall e \in E$) and a collection of subsets of A is examined. The problem is:

Find a minimum weight spanning tree T such that each subset of the vertices in the collection induces a complete star in T.

This problem is targeted to construction of a minimum cost (weight) communication tree network for a collection of (not necessarily disjoint) groups of end users (e.g., sensors, customers) such that each group induces a complete star. Thus, a broadcast communications network is obtained.

An illustrative numerical example for balanced spanning clustered tree is shown in Fig. 2.7 (e.g, [777]):

(i) an initial item set involves 24 items/elements $\{a_1, ..., a_{24}\}$;

(ii) three element type are are used: 1 (e.g., as a cluster head), 2 (e.g., as a retranslator node), and 3 (end-user node);

(iii) 6 balanced clusters are examined: X_1, X_2, X_3, X_4, X_5, and X_6;

(iv) each cluster contains 4 items: one item of type 1, one item of type 2, two items of type 3; and

(v) a spanning tree over the balanced clusters is considered.

Table 2.6. Some studies on clustered tree problems

No.	Study	Source(s)
1.	Problems:	
1.1.	Optimal stars-clustering-tree problem	[711]
1.2.	Optimal clustering tree problem	[710]
1.3.	Clustered spanning tree for weighted graph	[819]
1.4.	Minimum spanning trees and single linkage cluster analysis	[512]
1.5.	Clustered spanning tree (conditions for feasibility)	[538]
1.6.	Clustered Steiner tree problem	[1302,1305]
1.7.	Balanced clustering with tree-like structures over clusters	[774,777]
1.8.	NP-hard problems in hierarchical-tree clustering	[722]
2.	Some solving methods:	
2.1.	Fast quartet tree heuristic for hierarchical clustering	[337]
2.2.	Clustering algorithm for tree structure evaluation (fuzzy clustering analysis, intuitionistic fuzzy relation)	[189]
2.3.	Vertices removal for feasibility of clustered spanning tree	[539]
3.	Applications in communication networks:	
3.1.	Tree-cluster structure in WSN	[904]
3.2.	Tree-based clustering (TBC) for energy efficient WSNs	[691]
3.3.	Cluster-tree based routing in WSNs	[160,973]
3.4.	Cluster-tree based data dissemination routing protocol	[151]
3.5.	Cluster tree based self organization of virtual sensor networks	[159]
3.6.	Enhanced top-down cluster and cluster-tree formation algorithm for WSNs	[158]
3.7.	Efficient cluster-tree data collection scheme for large mobile WSNs	[1248]
3.8.	Cluster-tree based data gathering algorithm for WSNs	[1328]
3.9.	Efficient cluster tree topology operation and routing for IEEE 802.15.4-based smart grid networks	[695]
3.10.	Minimum routing cost clustered tree problem	[819]
4.	Some special applications:	
4.1.	Evaluation of college students' English performance considering Roche multiway tree clustering	[1323]
5.	Some dynamic problems:	
5.1.	Dynamic cluster scheduling for cluster–tree WSNs	[1117]
5.2.	Dynamic reconfiguration of cluster-tree WSNs to handle communication overloads	[824]
6.	Some studies in tree partitioning problems:	
6.1.	Mixed-integer linear programming (MILP) approaches for tree partitioning (for power networks)	[746]
6.2.	Balanced partitions of trees and applications (k-balanced partitioning)	[454]
6.3.	Max-min tree partitioning problems (shifting algorithms)	[1012]
6.4.	Cardinally constrained connected balanced partitions of trees under different criteria	[346]

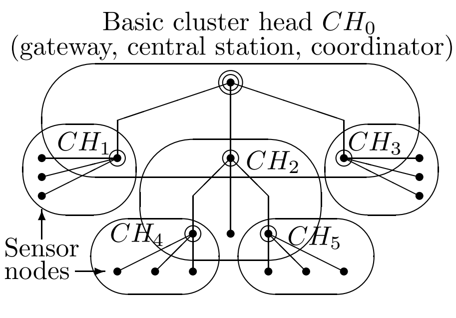


Fig. 2.6. Cluster–tree topology (WSN)

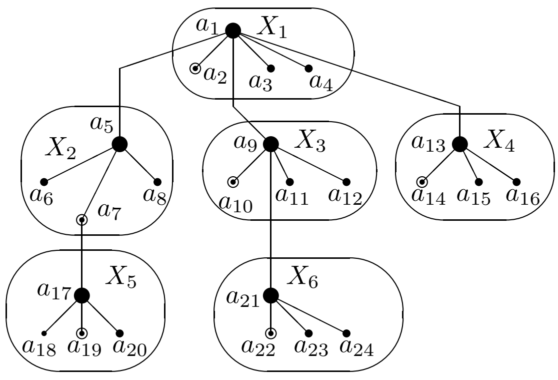


Fig. 2.7. Example of balanced clustered tree

The basic directions for modification/extension of the clustered tree problem(s) are the following: (1) multicriteria (multi-objective) problem formulations; (2) problems under uncertainty; (3) dynamic (multi-stage) problem formulations; and (4) usage of various kinds of estimates (e.g., ordinal estimates, vector-like estimates, fuzzy estimates, multiset-based estimates).

2.1.5. Capacitated clustering

The capacitated clustering problem (CCP) consists of forming a specified number of clusters or groups from a set of elements in such a way that the sum of the weights of the elements in each cluster is within some capacity limits, and the sum of the benefits between the pairs of elements in the same cluster is maximized (e.g., [111,302,388,513,782,783,845,875,929]). This problem is also known as the node capacitated graph partitioning problem [917]. The capacitated clustering problem (CPP) belongs to class of NP-hard combinatorial problems (e.g., [929]). An illustrative example of the basic capacitated clustering problem is depicted in Fig. 2.8.

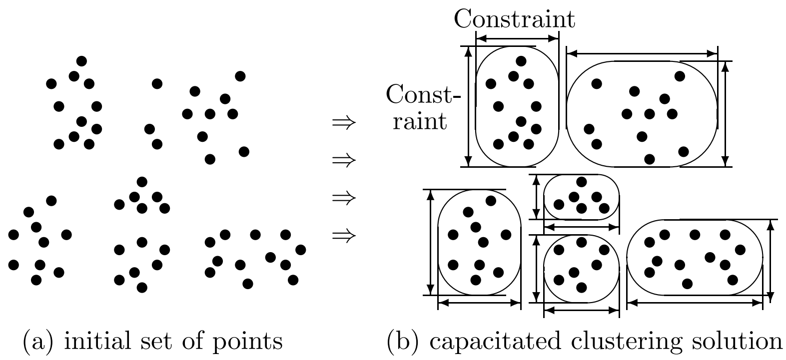


Fig. 2.8. Illustration for capacitated clustering

A short list of some basic capacitated clustering problems is pointed out in Table 2.7. Note this kind of clustering problems is close to various constrained clustering (e.g., [509]) (Table 2.7).

Table 2.7. Capacitated clustering and some close constrained clustering

No.	Problem/study	Source(s)
1.	Capatitated clustering problems:	
1.1.	Survey on the on the problem formulations and solving heuristics	[388]
1.2.	Basic capacitated clustering problem	[845,874,875,929]
1.3.	Capacitated centered clustering	[300–302,513,886]
1.4.	Multi-capacity clustering problem	[111]
1.5.	Heterogeneous capacitated clustering problems	[951]
1.6.	Large-scale capacitated clustering	[513]
1.7.	Fair-capacitated clustering	[1042]
2.	Some close constrained clustering problems/studies:	
2.1.	Constrained clustering (taxonomy, semi-supervised constrained clustering)	[509]
2.2.	Constrained clustering (advances in algorithms, theory, and applications)	[183]
2.3.	Combinatorial optimization approach to constrained clustering	[223]
2.4.	Data clustering with size constraints	[1414]
2.5.	Size-constrained clustering with MILP formulation	[1206]
2.6.	Constrained spectral clustering	[1271]
2.7.	Constrained clustering with weak label prior	[1389]
2.8.	Large-scale constrained clustering	[173]

The basic problem formulation of the capacitated clustering is as follows (e.g., [874]). Given a graph $G = (V, E)$ where V is a set of n nodes and E is a set of edges, let $w_i \geq 0$ be the weight of node $i \in V$ and let c_{ij} be the benefit of edge $(i, j) \in E$. The capacitated clustering problem (CCP) consists of partition V into p clusters in such a way that the sum of the weights of the elements in each cluster is within some integer capacity limits, L and U, and the sum of the benefits between the pairs of elements in the same cluster is maximized. The CCP can be formulated as a quadratic integer program with binary variables x_{ik} that take the value of 1 if element i is in cluster k and 0 otherwise.

$$\max \sum_{k=1}^{p} \sum_{i=1}^{n-1} \sum_{j>i}^{n} c_{ik} x_{ik} \, x_{jk} \qquad (2.12)$$

$$s.t. \quad \sum_{k=1}^{p} x_{ik} = 1, \quad i = \overline{1,n}; \qquad L \leq \sum_{i=1}^{n} w_i x_{ik} \leq U, \quad k = \overline{1,p}; \tag{2.13}$$

$$x_{ik} \in \{0,1\}, \quad i = \overline{1,n}, \quad k = \overline{1,p}. \tag{2.14}$$

The objective function adds the total benefit of all pairs of elements that belong to the same cluster. The first set of constraints forces the assignment of each element to a cluster. The second set of constraints forces the sum of the weights of the pairs of elements in the same cluster to be between L and U.

Some network applications of the capacitated clustering problems are: (i) partitioning of nodes in distributed computer networks and (ii) handover minimization in mobile wireless networks. Table 2.8 contains a list of basic solving approaches.

Table 2.8. Basic solving approaches

No.	Solving approach	Source(s)
1.	Basic methods (mainly – heuristics):	
1.1.	Greedy random adaptive memory programming search for capacitated clustering problems	[35]
1.2.	Scatter search heuristic for the capacitated clustering problem	[1106]
1.3.	Adaptive biased random-key GA with local search for capacitated centered clustering problem	[302]
1.4.	Tabu search for the capacitated clustering problem	[1410]
1.5.	Tabu search and GRASP for the capacitated clustering problem	[874]
1.6.	Randomized heuristics for the capacitated clustering problem	[875]
1.7.	Heuristic search to the capacitated clustering problem	[1410]
1.8.	Lagrangian relaxation approach for a large scale new variant of capacitated clustering problem	[1327]
1.9.	Parallel clustering search applied to capacitated centered clustering problem	[886]
1.10.	Reactive GRASP with path relinking for capacitated clustering	[388]
1.11.	Matheuristic for large-scale capacitated clustering	[513]
2.	Neighborhood search methods:	
2.2.	Variable neighborhood search (VNS) for capacitated clustering problem	[240]
2.2.	Iterated VNS for the capacitated clustering problem	[742]
2.3.	Neighborhood decomposition-driven VNS for capacitated clustering	[744]
3.	Evolutionary methods:	
3.1.	Genetic algorithms for capacitated clustering problem	[1137]
3.2.	Memetic algorithm for the capacitated clustering problem	[1410]
3.3.	Hybrid evolutionary algorithm for the capacitated centered clustering problem	[301]
4.	Hybrid methods:	
4.1.	Hybrid simulated annealing and tabu search (for capacitated clustering problems)	[974]
4.2.	HA-CCP: a hybrid algorithm for solving capacitated clustering problem	[845]
4.3.	Hybrid evolutionary algorithm for the capacitated centered clustering problem	[301]
4.4.	Clustering search algorithm as hybrid metaheuristic for capacitated centered clustering problem	[300]
4.5.	Hybrid metaheuristics for multi-capacity clustering problem	[111]

Related problems (e.g., maximum diversity grouping problem) and multicriteria capacitated clustering problems are described in [782].

2.1.6. k-center clustering problems

The basic k-center clustering problem is the following (e.g., [507,555,556]). A set of point (items) $A = \{a_1, ..., a_i, ..., a_n\}$ and metric (or proximity) $d(a_{i_1}, a_{i_2})$ $\forall a_{i_1}, a_{i_2} \in A$ are considered. A positive integer parameter $k > 0$ ($k < n$) is specified. The problem is:

Find a set of k center-points $B \subseteq A$ (i.e., $|B| = k$, a set B is a set of centers), such that the maximum distance of a point in A to its close point in B is minimized.

Evidently, the solution of the problem corresponds to formation of k clusters $(X_1, ..., X_\xi ..., X_k)$: each cluster X_ξ contains center $b_\xi \in B$ and close to b_ξ elements of A. The formal model is as follows:

$$price(B,A) = \max_{a_i \in A} \min_{b_\xi \in B} d(a_i, b_\xi). \qquad (2.15)$$

This k-center clustering problem is NP-hard [507].

The following basic versions of k-center clustering problems are considered (e.g., [555,556]):

1. In the continuous k-center clustering, the center can be located everywhere in the underlying space.

2. In discrete k-center clustering problem the k centers must be input points.

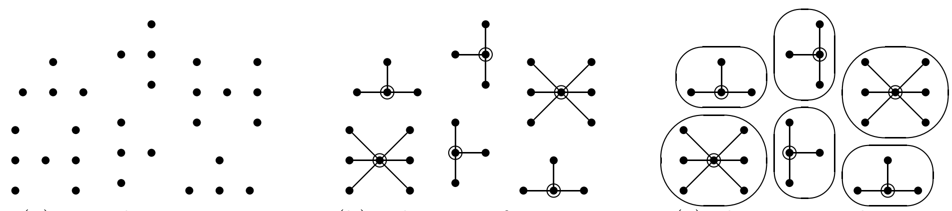
3. An alternative interpretation of k-center clustering is that like to cover the points by k balls, where the radius of the largest ball is minimized.

Some publications on k-center clustering problems and studies are listed in Table 2.9.

Table 2.9. k-center clustering problems and studies

No.	Problem/study	Source(s)
1.	Basic studies:	
1.1.	k-center clustering problems (continuous k-center clustering, discrete k-center clustering, diameter k-center)	[18,555,556]
1.2.	Fair k-center clustering (for data summarization)	[104,699]
1.3.	k-center clustering with outliers on massive data	[866]
1.4.	Fair k-center clustering in MapReduce and streaming settings	[194]
1.5.	On parallel k-center clustering	[351]
1.6.	Extreme k-center clustering	[186]
1.7.	Fair colorful k-center clustering	[638]
1.8.	Red-blue k-center clustering with distance constraints	[433]
1.9.	k-center clustering with outliers in sliding windows	[1007]
1.10.	k-center clustering with outliers in the MPC and streaming model	[195]
2.	Dynamic k-center clustering:	
2.1.	Fully dynamic k-center clustering	[284]
2.2.	Optimal fully dynamic k-center clustering (survey)	[187]
2.3.	Fully dynamic k-center clustering with outliers	[285]
2.4.	Optimal fully dynamic k-center clustering for adaptive & oblivious adversaries (survey)	[188]
2.5.	Fully dynamic k-center clustering in low dimensional metrics	[510]
2.6.	Fully dynamic consistent k-center clustering	[739]
3.	Some solving approaches:	
3.1.	Greedy algorithm for k-center clustering	[556]
3.2.	Greedy strategy works for k-center clustering with outliers and coreset construction	[401]
3.3.	Agglomerative algorithm for k-center clustering	[18]
3.4.	Scalable approximation algorithm for k-center fair clustering	[558]
3.5.	2-approximation algorithm for k-center clustering problem	[555]
3.6.	Streaming algorithms for k-center clustering with outliers and with anonymity	[883]
3.7.	Solving k-center clustering (with outliers) in MapReduce and streaming, almost as accurately as sequentially	[275]
3.8.	Exact global optimization algorithm based on reduced-space spatial branch and bound scheme (for the k-center clustering problem)	[1152]
3.9.	Pairwise fair and community-preserving approach to k-center clustering	[243]
3.10.	Corset-based streaming algorithms for k-center clustering problem with z outliers	[1007]
3.11.	Proximity search to compute k-center clustering	[556]

Fig. 2.9 illustrates a simplified numerical example of k-center clustering problem ($k = 6$).



(a) initial point set (b) selection of centers (c) clustering solution

Fig. 2.9. Illustration of k center clustering

Note the k-center clustering problem can be extended (e.g., by the following ways): (a) consideration of multicriteria problem statement (e.g., by using vector-like proximity for item pairs), (b) examination of the problem under uncertainty (i.e., probabilistic estimates of parameters, fuzzy set based estimates, multiset based estimates). (c) analysis of dynamic and/or online problems.

2.1.7. Dominating set based clustering

A recent author survey on dominating set based clustering problems is described in [775,776]. Let graph $G = (A, E)$ be a connected undirected graph, where A is a vertex/node set and E is a edge set. A dominating set of graph G is a vertex set $B \subseteq A$, such that every vertex $a \in A$ is either in B or there is a vertex $b \in B$ such that $(a, b) \in E$ (i.e., a is connected to w. A vertex of B is said to dominate itself and all adjacent vertices. The vertices from B are called dominators. Two illustrations of dominating sets are shown: (a) dominating set (Fig. 2.10) and (b) connected dominating set (Fig. 2.11).

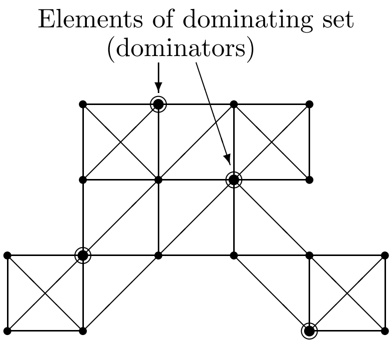


Fig. 2.10. Illustration for dominating set

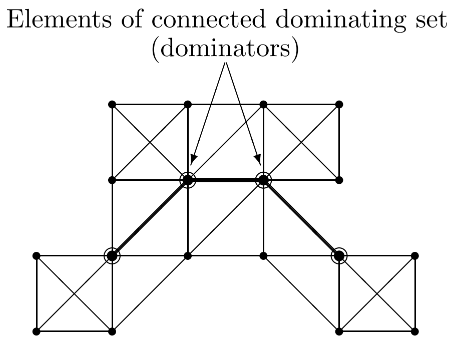


Fig. 2.11. Connected dominating set

Illustrations of dominating sets are shown: (a) initial set (Fig. 2.12), (b) dominating set (Fig. 2.13), (c) connected dominating set (Fig. 2.14), and (d) 2-connected dominating set (Fig. 2.15).

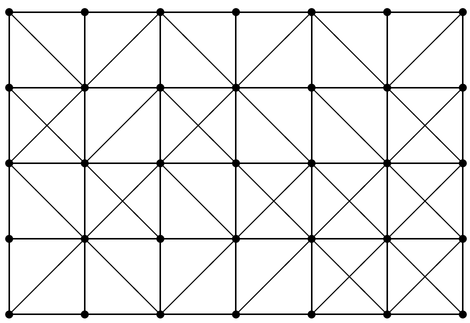


Fig. 2.12. Initial set

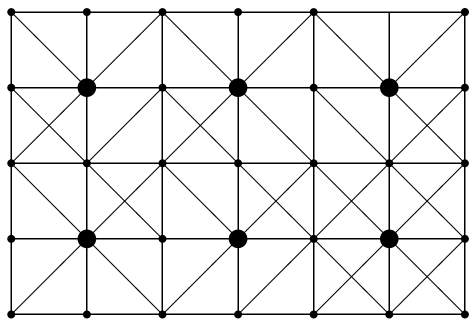


Fig. 2.13. Dominating set

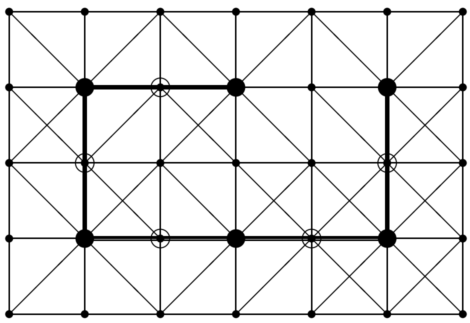


Fig. 2.14. Connected dominating set

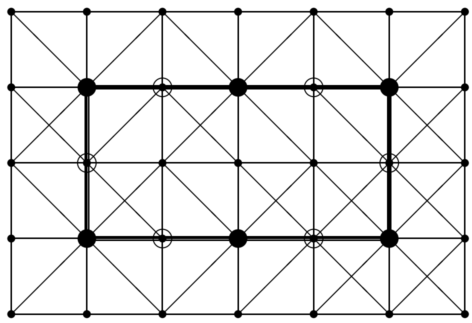


Fig. 2.15. 2-connected dominating set

An illustration for 2-connected 3-dominating set problem is shown in Fig. 2.16.

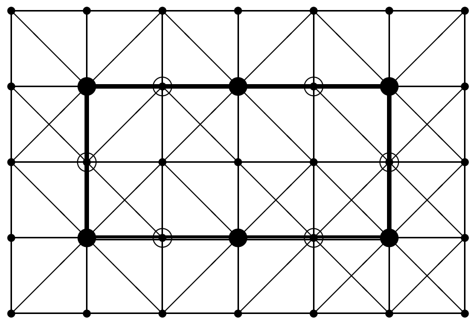


Fig. 2.16. 2-connected 3-dominating set

The vertices of the dominating set are used as clusterheads. Each vertex is assigned to a cluster corresponding to a vertex that dominates it (i.e., all vertices of the cluster).

Thus, the basic dominating set problem is combinatorial optimization problem:

Find the minimum sized dominating set for the initial graph.

This problem is NP-hard [482,563]. The problem to find the minimum sized connected dominating set for the initial graph is NP-hard as well [482,563]. The minimum connected DS problem is often used for defining a minimum size virtual backbone for Ad Hoc networks (e.g., [969]). Here, the following evident design scheme is used: (i) defining the set B (as set of clusterheads), (ii) allocation of the secondary network nodes (i.e., elements of $A \setminus B$) to clusterheads (i.e., elements of B).

Various exact methods and approximating algorithms (as heuristics) have been proposed for the problems above in (e.g., [412,519]).

Some basic versions of dominating set problems are listed in Table 2.10 (e.g., [412,482,519,563,1190, 1347]).

Table 2.10. Basic dominating set based problems

No.	Problem type	Source(s)
1.	Dominating set problem, minimum dominating set problem	[412,482,578]
2.	Connected dominating set problems (e.g., minimum connected dominating set, i.e., minimum cardinality of the dominating set)	[208,248,412,482,519] [908,969,1083,1105,1166] [1200,1297,1300,1406]
3.	Minimum size weakly-connected dominating sets	[42,87,305,307,1346]
4.	Total dominating set problems	[286,1105]
5.	Node weighted connected dominating set problem (e.g., vertex importance) (minimum weight connected dominating set problem)	[68,286,412,519,647] [818,1022,1245,1274,1406]
6.	k-connected m-dominating set problem	[356,792,1132,1212]
7.	Minimum weight k-connected m-fold dominating set (minimum weight (k,m)-CDS problem)	[1151]
8.	Optimal degree constrained minimum-weight connected dominating set problem (network backbone formation)	[48]
9.	Steiner connected dominating set problem	[49,519,898,1298]
10.	Node weighted Steiner connected dominating set problem (minimum weight Steiner connected dominating set problem)	[44,519]
11.	Edge weighted connected dominating set problem	[519]
12.	Connected k-hop dominating set problems	[964,1301,1326,1399]
13.	Dominating sets and connected dominating sets in dynamic graphs	[577]

Some research on dominating set problem based clustering are listed in Table 2.11.

Table 2.11. Dominating set problem based clustering

No.	Problem type/study	Source(s)
1.	Dominant-set clustering (review)	[252]
2.	Dominant sets and hierarchical clustering	[1001]
3.	Dominant sets and pairwise clustering	[1002]
4.	Connected dominating set based clustering algorithm (in MANET)	[1228]
5.	Simultaneous clustering and outlier detection using dominant sets	[1364]
6.	Automated multi-subject fiber clustering of mouse brain using dominant sets	[404]
7.	Constrained dominant sets for retrieval	[1365]
8.	DSLib: an open source library for the dominant set clustering method	[1244]

2.1.8. Domatic partition problem

The special domatic partition problem in networks (maximization of domatic number) is examined as partition of vertices into disjoint dominating sets (e.g., [452,482,775,1348]). The dominating number is the maximum number of such sets. Here a given graph $G = (A, E)$ corresponds to a network (e.g., WSN). Dominating set $D \subseteq A$ is a subset of vertices such that each node $a \in A$ is either in D or has a neighbor in D. A domatic partition (DP) is a partition $D = \{D_1, ..., D_i, ..., D_t\}$ of A such that D_i ($\forall i = \overline{1,t}$ is a dominating set of G, where t is called domatic number, which is the number of disjoint dominating sets.

In the domatic partition problem, a domatic partition with maximal domatic number is searched for. The problem is NP-hard (e.g., [452,482]).

An simplified numerical example illustrates the domatic partition problem (Fig. 2.17):

(a) initial vertex set: $A = \{1, 2, 3, 4, 5, 6, 7\}$,

(b) domatic partition: $D = \{D_1, D_2, D_3\}$, $D_1 = \{1, 4\}$, $D_2 = \{2, 7\}$, $D3 = \{3, 5, 6\}$.

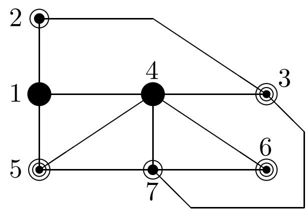


Fig. 2.17. Example of domatic partition

Several types of the domatic partition problems are listed in Table 2.12.

Table 2.12. Some types of domatic partition problems

No.	Study	Source(s)
1.	Basic domatic partition problem	[452,482]
2.	Domatic partition problem on special simplified graphs (e.g., perfect graphs, interval graphs, etc.)	[660,1058]
3.	Domatic partitions of unit disk graphs	[989]
4.	Independent domatic partition problem	[858]
5.	k-domatic partition problem (k-dominating set is a subset D of nodes such that every graph node is distance at most k from D	[1008]

2.1.9. Clustering in multi-partite graphs

In [294] optimal clustering of multipartite graphs is examined as follows (clique partitioning). A graph $G = (A, E)$ is considered. The problem is:

Find a partitioning A into a disjoint union of cliques by adding or removing a minimum number $z(G)$ of edges.

This problem is NP-hard. Some studies on clustering of multi-partite graphs (clique partitioning) are listed in Table 2.13.

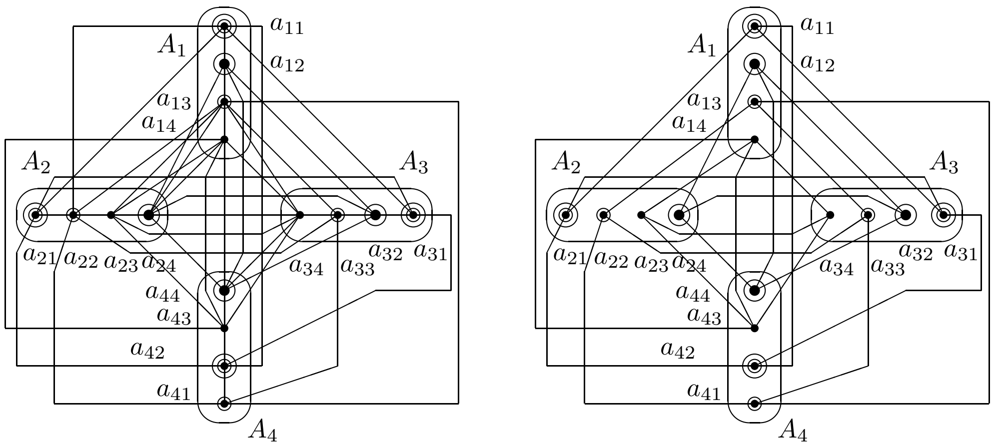
Table 2.13. Some studies on clustering of multi-partite graphs

No.	Study	Source(s)
1.	Optimal clustering of multipartite graphs (clique partitioning)	[294]
2.	Near optimal LP rounding algorithm for correlation clustering on complete and in complete k-partite graphs	[303]
3.	Clique partitioning problem (branch and bound method)	[295]
4.	Maximum matching in complete multi-partite graphs (k-partite clique; maximizing the switch cost in optical networks)	[1128]
5.	Detecting k-balanced trusted cliques in signed social networks (clustering in k-partite clique)	[554]
6.	Incremental k-clique clustering (in dynamic social networks)	[415]

On the other hand the problem can be considered as searching for disjoint morphological cliques (e.g., [763,767]). A corresponding simplified illustration of clustering problem in multi-partite graph (four-partite graph) is depicted in Fig. 2.18. The initial four-partite graph $G = (A, E)$ is: part 1: $A_1 = \{a_{11}, a_{12}, a_{13}, a_{14}\}$, part 2: $A_2 = \{a_{21}, a_{22}, a_{23}, a_{24}\}$, part 3: $A_3 = \{a_{31}, a_{32}, a_{33}, a_{34}\}$, part 4: $A_4 = \{a_{41}, a_{42}, a_{43}, a_{44}\}$. The edge set E is presented in Table 2.14. The following four clusters (morphological cliques) are obtained (Fig. 2.18b): (i) $X_1 = \{a_{11}, a_{21}, a_{31}, a_{42}\}$, (ii) $X_2 = \{a_{12}, a_{24}, a_{32}, a_{44}\}$, (iii) $X_3 = \{a_{13}, a_{22}, a_{33}, a_{41}\}$, and (iv) $X_4 = \{a_{14}, a_{23}, a_{34}, a_{43}\}$.

Table 2.14. Edge set of four-partite graphs $E = \{(a_{i_1k_1}, a_{i_2k_2})\}$

$a_{i_1k_1}$	$a_{i_2k_2}$:	a_{11}	a_{12}	a_{13}	a_{14}	a_{21}	a_{22}	a_{23}	a_{24}	a_{31}	a_{32}	a_{33}	a_{34}	a_{41}	a_{42}	a_{43}	a_{44}
a_{11}			1			0	0	0	0	0	0	0	0	0	0	0	0
a_{12}				1		0	0	0	0	0	0	0	0	0	0	0	0
a_{13}					1	0	0	0	0	0	0	0	0	0	0	0	0
a_{14}						0	0	0	0	0	0	0	0	0	0	0	0
a_{21}							1			0	0	0	0	0	0	0	0
a_{22}								1		0	0	0	0	0	0	0	0
a_{13}									1	0	0	0	0	0	0	0	0
a_{14}										0	0	0	0	0	0	0	0
a_{31}											1			0	0	0	0
a_{32}												1		0	0	0	0
a_{33}													1	0	0	0	0
a_{34}														0	0	0	0
a_{41}															1		
a_{42}																1	
a_{43}																	1
a_{34}																	



(a) initial graph (b) clustering solution

Fig. 2.18. Illustration of clustering in multi–partite graph (morphological cliques)

Evidently, the clustering in multi-partite problem can may be extended by some ways, for example: (a) examination of the problem as multi-objective statement; (b) examination of the problem under uncertainty (i.e., fuzzy set estimates, multiset based estimates, probabilistic statements); and (c) examination of dynamic/online problems.

2.1.10. k-edge colored clustering

An author material on the k-edge colored clustering problem was published in [779]. A basic application of the problem is considered in optical networks (e.g., colors correspond to wavelengths). Here, an edge colored graph $G = (A, B)$ is given; $A = \{a_1, ..., a_j, ..., a_n\}$ is the set of vertices/nodes, $B = \{b_1, ..., b_i, ..., b_m\}\}$ is the set of edges. There are a set of integers (called colors) $C = \{c_1, ..., c_\mu, ..., c_k\}$. Each edge $b \in B$ has the assigned color $c_\mu(b)$ and weight w_b. The Max k-Edge Colored Clustering problem (MAX-k-EC) can be described as follows (e.g., [29,73,101]):

To assign an available color from set $C = \{c_1, ..., c_\mu, ..., c_k\}$ for every graph vertex so as to create at most k clusters. Each cluster corresponds to the subgraph induced by the vertices colored with the same color. For the coloring of the graph vertices, an edge is called matched (or stable) if its color is the same as the color of both its extremities. The problem goal is to maximize the total weight of the matched edges of the graph.

The k-edge colored clustering problem model is the following (e.g., [73,101]). Consider two sets of variables: (i) z_b, $b \in B$ and (ii) x_{ac_μ}, $a \in A$, $c_\mu \in C$ ($\mu = \overline{1,k}$); where $z_b = 1$ if both endpoints of e are colored with the same color as b and $z_b = 0$ otherwise and $x_{ac_\mu} = 1$ if a is colored with color c_μ and $x_{ac_\mu} = 0$ otherwise. The following integer linear program (ILP) for MAX-k-EC is examined (here $c(b)$ corresponds to color c_μ that was assigned to edge $b \in B$):

$$\max \sum_{b \in B} w_b z_b \quad s.t. \sum_{\mu=1}^{k} x_{ac_\mu} = 1, \quad \forall a \in A; \tag{2.16}$$

$$z_b \leq min\{x_{a_1 c(b)}, x_{a_2 c(b)}\} \quad \forall b = (a_1, a_2) \in B; \quad x_{ac_\mu}, z_b \in \{0, 1\}, \ \forall a \in A, \ c_\mu \in C, \ b \in B. \tag{2.17}$$

The problem belongs to class of NP-hard problems. Some special methods have been proposed for the problem (heuristics, polynomial time approximate algorithms, etc.) (e.g., [29,73,101]).

An illustrative numerical example of the problem is the following (from [779]). Here an initial edge-colored graph is considered ($C = \{c_1, ..., c_4\}$) (Table 2.15, Fig. 2.19a).

Table 2.15. Edges of graph $G = (A, B)$

No.	Edge $b \in B$	Weight w_b	Edge color $c(b)$	Binary variable (selection) $z(b)$
1.	$b_1 = (a_1, a_2)$	$w_{b_1} = 0.5$	c_1	0
2.	$b_2 = (a_1, a_5)$	$w_{b_2} = 0.9$	c_1	1
3.	$b_3 = (a_2, a_3)$	$w_{b_3} = 1.2$	c_4	1
4.	$b_4 = (a_2, a_6)$	$w_{b_4} = 0.4$	c_1	0
5.	$b_5 = (a_3, a_4)$	$w_{b_5} = 0.6$	c_2	0
6.	$b_6 = (a_3, a_7)$	$w_{b_7} = 0.3$	c_3	0
7.	$b_7 = (a_4, a_6)$	$w_{b_6} = 0.9$	c_2	1
8.	$b_8 = (a_4, a_8)$	$w_{b_8} = 0.5$	c_1	0
9.	$b_9 = (a_4, a_9)$	$w_{b_9} = 0.4$	c_4	0
10.	$b_{10} = (a_5, a_7)$	$w_{b_{10}} = 1.0$	c_1	1
11.	$b_{11} = (a_6, a_7)$	$w_{b_{11}} = 0.2$	c_4	0
12.	$b_{12} = (a_7, a_8)$	$w_{b_{12}} = 0.5$	c_2	0
13.	$b_{13} = (a_8, a_9)$	$w_{b_{13}} = 1.1$	c_3	1

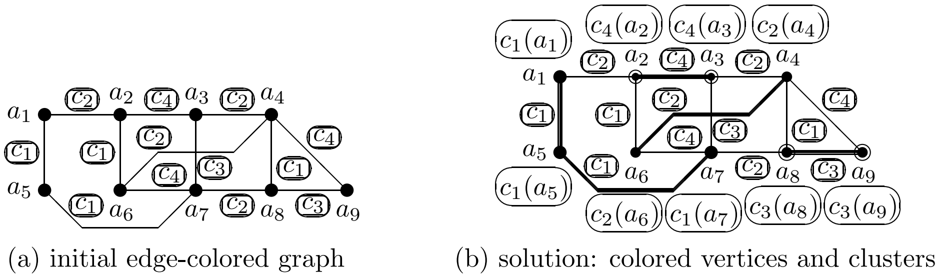


Fig. 2.19. Max k-edge colored clustering (example)

Table 2.16. Vertices of graph $G = (A, B)$ (solution)

No.	Vertex $a_j \in A$	Assigned vertex color c_{a_j}	Cluster $X(\mu)$ (Fig. 2.19)
1.	a_1	c_1	X_1
2.	a_2	c_4	X_2
3.	a_3	c_4	X_2
4.	a_4	c_2	X_3
5.	a_5	c_1	X_1
6.	a_6	c_2	X_3
7.	a_7	c_1	X_1
8.	a_8	c_3	X_4
9.	a_9	c_3	X_4

The obtained clusters are (clustering solution is $\widetilde{X} = \{X_1, X_2, X_3, X_4\}$ ($X_\mu \subseteq A \ \forall \mu = \overline{1,4}$, here $|X_{\mu_1} \bigcup X_{\mu_2}| = 0 \quad \forall \mu_1 \neq \mu_2$) (Fig. 2.19b, Table 2.15, Table 2.16):
(i) $X_1 = \{a_1, a_5, a_7\}$, color c_1; (ii) $X_2 = \{a_2, a_3\}$, color c_4;
(iii) $X_3 = \{a_4, a_6\}$, color c_2; (iv) $X_4 = \{a_8, a_9\}$, color c_3.

The basic k-edge coloring problems (while taking into account clustering) are the following: (1) compact k-edge-coloring [85]; (2) cyclic compact k-edge-colorings [937]; (3) bounded max-vertex-coloring problem [157]; (4) clustering on k-edge-colored graphs [100]; (5) maximum k-edge colored clustering [29,73]; (6) alternating path and colored clustering [258]; and (7) vertex coloring edge partitions [19].

A multicriteria version of the k-edge colored clustering problem is considered in [779].

2.1.11. Partition coloring problem

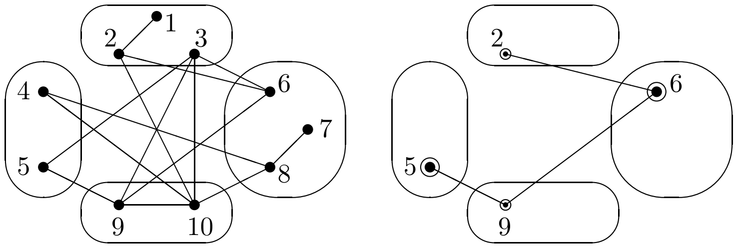
The partition coloring problem or selective graph coloring problem (i.e., selective graph clustering over clustered graph) is considered as the following [220,383,469,473,584,788,966]. This problem corresponds to routing and wavelength assignment in all-optical networks (i.e., computation of alternative routes for the light paths, followed by the solution of a partition colorings problem in a conflict graph) (e.g., [788,836,966]).

The problem formulation is as follows. Given a non-directed graph $G = (V, E)$, where V is the set of vertices (nodes) and E is the set of edges. Let $\{V_1, V_2, ..., V_q\}$ be a partition of V into q subsets with $V = \bigcup_{\iota=1}^{q} V_\iota$ and $|V_{\iota_1} \bigcap V_{\iota_2}| = 0 \ \ \forall \iota_1, \iota_2 = 1, 2, ..., q$ with $\iota_1 \neq \iota_2$. Clearly, V_ι ($\forall \iota = \overline{1,q}$) is a graph part or a graph component. The partition coloring problem is:

Find a subset $V' \subseteq V$ such that $|V' \bigcap V_\iota| = 1 \ \forall \iota = \overline{1,q}$ (i.e., V' contains one vertex from each component V_ι), and the chromatic number of the graph induced in G by V' is minimum.

Evidently, the problem is a generalization of the graph coloring problem and belongs to class of NP-hard problems (e.g., [788]). Several formal models for this problem have been proposed: (a) binary integer programming problem (e.g., [469,584]), (b) model based on the independent set problem [584], and (c) two integer programming formulations using representatives [152].

Fig. 2.20 depicts an instance of partition coloring problem (graph with ten vertices and four graph parts). Here, the resultant colorings are (two colors: c_1, c_1):
$Q^1 =< 2(c_1), 6(c_2), 9(c_1), 5(c_2) >$, $Q^2 =< 2(c_2), 6(c_1), 9(c_2), 5(c_1) >$.



(a) initial graph instance (b) solution (two colors)

Fig. 2.20. Instance of partition coloring problem

Some studies of partition coloring problems/selective graph coloring and their applications in communication networks are listed in Table 2.17. Some solving approaches for the partition coloring problem are listed in Table 2.18. An application example of partition coloring problem in optical communication network is described in [770].

Table 2.17. Some studies of partition coloring/selective graph coloring problems

No.	Study	Source(s)
1.	Routing and wavelength assignment by partition coloring	[966]
2.	Partition independent set and reduction based approach for partition coloring problem	[1419]
3.	Partition coloring or selective coloring problem (clustered graphs)	[220]
4.	Branch-and-price approach for the partition coloring problem	[584]
5.	Some applications of the selective graph coloring problem	[382]
6.	Exact algorithm for the partition coloring problem (branch-and-price algorithm)	[473]
7.	Memetic algorithm for the partition graph coloring problem	[1020]
8.	Branch-and-cut algorithm for partition coloring	[469]
9.	Complexity of the selective graph coloring problem in some special classes of graphs	[381]
10.	Minimum and maximum selective graph coloring problems in some graph classes	[383]
11.	Decomposition approach to solve the selective graph coloring problem in some perfect graph families	[1112]
12.	Exact cutting algorithm to solve the selective graph coloring problem in perfect graphs	[1113]
13.	Complexity of the partition coloring problem	[527]
14.	Memetic algorithm for two distinct solution representations for the partition graph coloring problem	[1021]
15.	Improved hybrid ant-local search algorithm for the partition graph coloring problem	[463]
16.	Selective graph coloring in some special classes of graphs	[380]
17.	Partitioning of vertices into clusters as a dual problem to vertex coloring	[609]

Table 2.18. Algorithms for partition coloring problem

No.	Approach	Source(s)
1.	Branch-and-price approach	[469,473,584]
2.	Branch-and-cut algorithm	[152,469]
3.	Tabu search heuristic	[966]
4.	Two-phase heuristic	[966]
5.	Engineering heuristics	[788,836]
6.	Partition independent set and reduction based approach	[1419]
7.	Exact cutting algorithm	[1113]
8.	Decomposition approach	[1112]
9.	Improved hybrid ant-local search algorithm	[463]
10.	Memetic algorithm	[1020,1021]

2.1.12. Cluster editing problems

In recent decades, the cluster editing problems (CEPs) are actively examined (e.g., [122,182,212,214, 278,377,514,523]). The authors survey on cluster editing problem is contained in [784]. Note the classical cluster editing problem is often studied as correlation clustering (e.g., [36,166,190,340,905,1260]). In the field of cluster editing problem two close NP-complete edge modification problems are under examination: (1) cluster editing and (2) cluster deletion (e.g., [377,514]). Here, the problem (optimization version) consists in finding the fewest changes of edge set (i.e., the minimum number of edge changes; edge addition, edge deletion) of an initial graph to obtain a new graph that is a vertex–disjoint union of cliques/clusters. In cluster edition problem, edge additions and deletions are considered; in cluster deletion problem, only edge deletions are considered.

An illustration scheme of the cluster editing problems domain is depicted in Fig. 2.21.

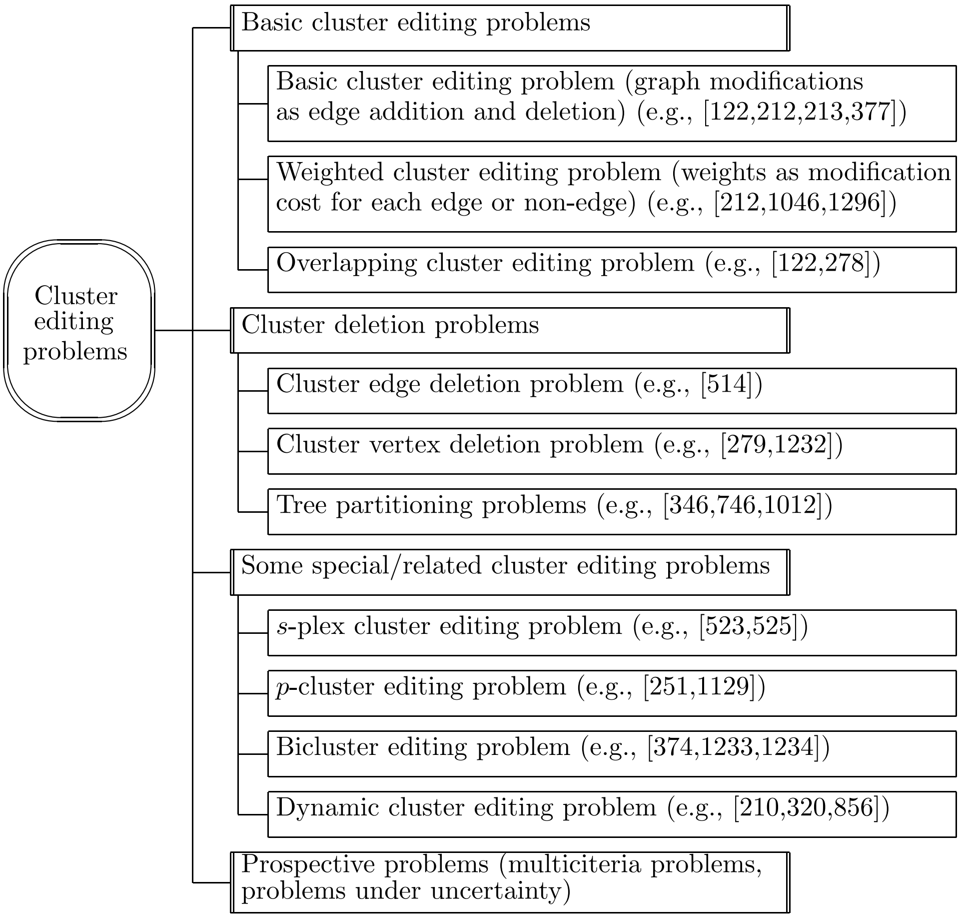


Fig. 2.21. Illustration for cluster editing problem domain

The cluster editing problems can be used as a basis for network partitioning, network transformations/modifications. The cluster editing problems are often used as some components in various combinatorial solving frameworks (e.g., graph modification problems).

The Cluster Edge Editing Problem (CEP) can be defined as follows (e.g., [182,251,523]):

Given a graph $G = (A, E)$ (A is the set of vertices, E is the set of edges) transform G into a vertex-disjoint union of cliques by inserting and deleting a minimum number of edges, i.e., by making a minimum number of editions in G.

The cliques of a solution are considered as clusters (a cluster with only one vertex is a singleton) and a graph where each component is a clique is a cluster graph.

An illustrative numerical example for CEP is depicted in Fig. 2.22:

(a) initial graph (Fig. 2.22a),

(b) the optimal solution by 10 editions/modification operations (6 deletion, 4 addition) as vertex-disjoint union of three cliques/clusters (Fig. 2.22b).

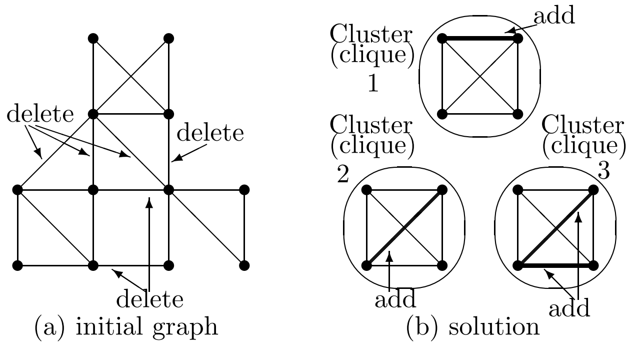


Fig. 2.22. Illustration for cluster editing problem

Table 2.19 contains a list of basic solving approaches.

Table 2.19. Basic solving approaches

No.	Study	Source(s)
1.	Some surveys:	
1.1.	Theoretical study of cluster editing problems (equivalent problems to cluster editing problem)	[166]
1.2.	Efficient algorithms for cluster editing	[182]
2.	Enumerative exact methods:	
2.1.	Branch-and-bound algorithm for cluster editing	[207]
2.2.	Branch-and-cut approaches for p-cluster editing	[251]
2.4.	Exact methods for weighted cluster editing	[1046]
3.	Heuristics, metaheuristics, approximation algorithms:	
3.1.	Heuristics for weighted cluster editing	[1046]
3.2.	Layout based heuristic for weighted cluster editing	[1296]
3.4.	Hybrid heuristic for the overlapping cluster editing problem	[278]
3.5.	Heuristics/metaheuristics for bicluster editing problem	[374]
4.	Polynomial time algorithms:	
4.1.	Polynomial algorithm for cluster vertex deletion problem on block graphs/split graph	[266]
4.3.	Polynomial algorithm for cluster vertex deletion problem on bounded tree width graphs	[1100]
4.5.	Polynomial algorithm for $(1,1)$-Cluster Editing problem	[535]
4.7.	Polynomial time algorithm for cluster editing problem on proper interval graphs	[826]
5.	Polynomial time approximation schemes (PTAS):	
5.1.	PTAS for cluster editing problem on planar graphs	[196]
5.3.	Polynomial time approximation algorithms for cluster editing problem with clusters of small sizes	[707]
6.	Parameterized algorithms:	
6.2.	Parameterized algorithms for cluster editing	[212]
6.6.	Faster parameterized algorithm for cluster vertex deletion	[1232]
6.7.	Faster parameterized algorithms for bicluster editing	[1233,1234]
6.8.	Fixed-parameter algorithms for bicluster editing	[740]
7.	Special approaches:	
7.1.	Graph-modeled data clustering (exact algorithm for clique generation)	[514]
7.2.	Effective linear kernelization for cluster editing	[523]
7.3.	Two-phase solving strategy for CEP based on set partitioning	[182]

Some problem statements are as follows. The basic designations are considered for the finite undirected graph $G=(A,E)$ (or $G=(A(G),E(G))$):

(i) $A(G)=\{a_1,...,a_i,...,a_n\}$ is the set of vertices;

(ii) $E(G)=\{(a_i,a_j)\}$ $(a_i,a_j \in A)$ is the set of edges $E(G) \subseteq \{A \times A\}$;

(iii) $\overline{E}(G)$ is the set of vertex pair which have no edges ($\overline{E}(G) \subseteq \{A \times A\}$): $E \bigcup \overline{E} = \{A \times A\}$ and $|E \bigcap \overline{E}| = 0$.

The mathematical formulation (integer linear programming ILP model) of cluster edge editing problem (CEP) was proposed in [291]. Here a graph G is a cluster graph if and only if G does not contain the graph P_3 (a path formed by three vertices) as an induced subgraph. For each two vertex pair a_i, a_j ($\forall a_i, a_j \in A(G)$) with $i < j$, let x_{ij} be a binary variable such that $x_{ij} = 0$ if and only if vertices a_i and a_j belong to the same clique (cluster) in a final solution. The minimization problem formulation is:

$$\min \ [\ C^d = \sum_{i<j,\ (a_i,a_j)\in E(G)} x_{ij} \ + \ C^a = \sum_{i<j,\ (a_i,a_j)\overline{\in} E(G)} (1 - x_{ij})\ ] \qquad (2.18)$$

$$s.t. \quad x_{ik} \leq x_{ij} + x_{jk}, \quad x_{ij} \leq x_{ik} + x_{jk}, \quad x_{jk} \leq x_{ij} + x_{ik}, \quad i < j < k \qquad (2.19)$$

$$x_{ij} \in \{0, 1\} \quad i < j \qquad (2.20)$$

Note that the objective function (2.18) minimizes the number of edges that are converted into non-edges (C^d, i.e., deleted edges) plus the number of non-edges that are converted into edges (C^a, i.e., added edges). There are $O(n^3)$ triangle inequalities (2.19) that eliminate the induced subgraphs isomorphic to P_3.

The Weighted Cluster Edge Editing problem is examined as well (e.g., [212,1046,1296]). Here a non-negative weight $w_{i,j}$ for each vertex pair ($\forall a_i, a_j \in A(G)$, i.e., for edges and for non-edges) is considered:

$$\min \ [\ C^{dw} = \sum_{i<j,\ (a_i,a_j)\in E(G)} w_{i,j}\ x_{ij} \ + \ C^{aw} = \sum_{i<j,\ (a_i,a_j)\overline{\in} E(G)} w_{i,j}\ (1 - x_{ij})\ ] \qquad (2.21)$$

$$s.t. \quad x_{ik} \leq x_{ij} + x_{jk}, \quad x_{ij} \leq x_{ik} + x_{jk}, \quad x_{jk} \leq x_{ij} + x_{ik}, \quad i < j < k \qquad (2.22)$$

$$x_{ij} \in \{0, 1\} \quad i < j \qquad (2.23)$$

Note that the objective function (2.21) minimizes the weighted number of edges that are converted into non-edges (C^{dw}) plus the weighted number of non-edges that are converted into edges (C^{aw}).

A prospective multicriteria problem formulation is based on using vector-like weights of vertex pairs: $\overline{w}_{ij} = (w^1_{ij}, ..., w^{\xi}_{ij}, ..., w^{\lambda}_{ij})$ (for each vertex pair $\forall a_i, a_j \in A(G)$, i.e., for edges and for non-edges). The following multicriteria problem can be examined:

$$\min \ \overline{C}^{d\overline{w}} = (\sum_{i<j,\ (a_i,a_j)\in E(G)} w^1_{ij}\ x_{ij}, ...,$$

$$\sum_{i<j,\ (a_i,a_j)\in E(G)} w^{\xi}_{ij}\ x_{ij}, ..., \sum_{i<j,\ (a_i,a_j)\in E(G)} w^{\lambda}_{ij}\ x_{ij}\ ) \qquad (2.24a)$$

$$\min \ \overline{C}_{a\overline{w}} = (\sum_{i<j,\ (a_i,a_j)\overline{\in} E(G)} w^1_{ij}\ (1 - x_{ij}), ...,$$

$$\sum_{i<j,\ (a_i,a_j)\overline{\in} E(G)} w^{\xi}_{ij}\ (1 - x_{ij}), ..., \sum_{i<j,\ (a_i,a_j)\overline{\in} E(G)} w^{\lambda}_{ij}\ (1 - x_{ij})\ ) \qquad (2.24b)$$

$$s.t. \quad x_{ik} \leq x_{ij} + x_{jk}, \ x_{ij} \leq x_{ik} + x_{jk}, \ x_{jk} \leq x_{ij} + x_{ik}, \quad i < j < k \qquad (2.25)$$

$$x_{ij} \in \{0, 1\} \quad i < j. \qquad (2.26)$$

Here weighted λ-component vector objective functions are used: $\overline{C}^{d\overline{w}}$ and $\overline{C}^{a\overline{w}}$.

Two basic solving approaches can be considered:

(a) analysis of an integrated (e.g., by vector components) additive objective function: $\min\ (\overline{C}^{d\overline{w}} + \overline{C}^{a\overline{w}})$;

(b) consideration of two-part vector objective function: $\{\ \min\ \overline{C}^{d\overline{w}}, \min\ \overline{C}^{a\overline{w}}\ \}$.

The extended set of the objective functions for the cluster editing problems is presented in Table 2.20.

Table 2.20. Objective functions for cluster editing problem, algorithm estimates

No.	Objective function, algorithm estimate analysis	Notation	Source(s)
1.	Deletion criteria:		
1.1.	The number of edge deletion operations	C^{d}	[212,213,377,514,523]
1.2.	The weighted number of edge deletion operations	C^{dw}	[1046,1296]
2.	Addition criteria:		
2.1.	The number of vertex pair (edge) addition operations	C^{a}	[212,213,377,514,523]
2.2.	The weighted number of vertex pair (edge) addition operations	C^{aw}	[1046,1296]
3.	Criteria for weighted problems (i.e., weights of edge and non-edges):		
3.1.	Vector criteria of edge addition	$\overline{C}^{a\overline{w}}$	[784]
3.2.	Vector criteria of edge deletion	$\overline{C}^{d\overline{w}}$	[784]
4.	The quality of dynamic clustering solution (dynamic problem)	C^{dyn}	[770,856]
5.	The quality of multi-stage (trajectory) clustering solution	C^{traj}	[768]
6.	Complexity of procedures for cluster editing solving process (e.g., polynomial approximate algorithms/heuristics, enumerative methods)	C^{proc}	[13,466,834]

2.1.13. Cluster routing problems

The general cluster routing problem is examined in [631,1387]. Here, an edge-weighted complete undirected graph $G = (V, E, c)$ is considered (V is the set of vertices, E is the set of edges, the weight function for edges c). The vertex set V is partitioned into k clusters $\{C_1, \ldots , C_k\}$. Subsets of vertices $V' \subseteq V$ and edges $E' \subseteq E$ are examined. The weight function c satisfies the triangle inequality. Here the goal is to find a minimum cost walk T that visits each vertex in V' only once, traverses every edge in E' at least once and for every $\forall i \in \{1, ..., k\}$ all vertices of C_i are traversed consecutively.

Cluster-based optimization approach for VRP is described in [406]

Table 2.21 contains a list of cluster routing studies in communications. The basic idea (i.e., solving scheme) is as follows (i.e., design of a two-layer network topology) (Fig. 2.23):

(1) dividing the initial area into clusters,
(2) selection/assignment of cluster heads (CHs) (in each cluster),
(3) design of the routes for cluster heads (e.g., via base station, as backbone),
(4) for each cluster: connection of the leaf nodes (items-users) to cluster heads.

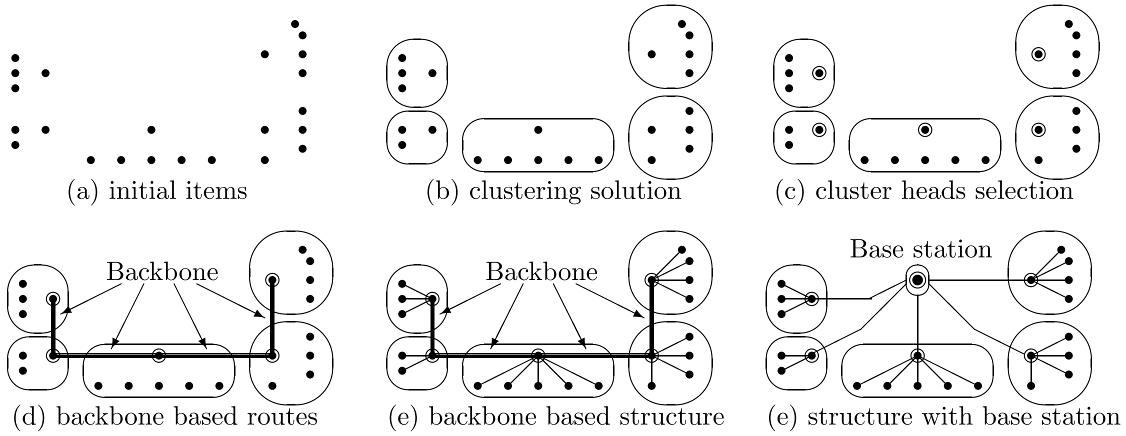


Fig. 2.23. Illustration for cluster routing

Table 2.21. Cluster routing problems and close problems (communications applications)

No.	Study	Source(s)
1.	Surveys on cluster routing:	
1.1.	The general cluster routing problem	[631,1387]
1.2.	Survey on cluster based routing protocols in WSNs (taxonomy of protocols)	[1170]
1.3.	Survey on cluster-based routing protocols in WSNs	[965]
1.4.	Survey on cluster-based routing protocols in WSNs	[832]
1.5.	Cluster-based routing protocols in WSNs (survey based on methodology)	[445]
1.6.	Cluster based routing protocols for wireless sensor networks (overview)	[50]
1.7.	Survey on the taxonomy of cluster-based routing protocols for homogeneous WSNs	[938]
2.	Basic cluster-based routing methods in communication:	
2.1.	RSSI cluster routing method (in cluster-based WSNs)	[580]
2.2.	Energy-efficient clustering-based mobile routing algorithm for WSNs	[662]
2.3.	Cluster-based approach for routing in dynamic networks	[717]
2.4.	QoS-aware and heterogeneously clustered routing protocol for WSNs	[93]
2.5.	Clustering routing protocol for energy balance of WSN based on simulated annealing and genetic algorithm	[1378]
2.6.	Energy aware hierarchical cluster-based routing protocol for WSNs	[673]
2.7.	Clustering routing algorithm based on improved ant colony optimization for underwater WSNs	[1313]
3.	Multi-hop cluster-based routing approaches:	
3.1.	Multi-hop cluster based routing approach for WSNs	[118]
3.2.	Multi-hop cluster-based routing protocols in WSNs	[445]

2.1.14. Clustered traveling salesman problem

Let $G = (A, E)$ be a complete undirected graph with vertex set A, edge set E and let $H =< G; S >$ be a hypergraph, where S is a set of not necessarily disjoint clusters S_1,..., S_m, $S_i \subseteq A$ $\forall i = \overline{1, m}$ such that $\bigcup_{i=1}^{m} S_i = A$.

The clustered traveling salesman problem (CTSP) is considered as the following (e.g., [537]):

Find a shortest Hamiltonian path that visits each one of the vertices once, such that the vertices of each cluster are visited consecutively.

Application of the problem can be considered as to find a minimal length route.

Table 2.22 contains a list of some clustered TSP studies.

Table 2.22. Some studies in clustered TSPs

No.	Study	Source(s)
1.	Problems:	
1.1.	Clustered TSPs	[330]
1.2.	The symmetric clustered TSP	[645]
1.3.	The clustered traveling salesman tour and path problems	[105]
1.4.	Clustered generalized TSP	[164,676]
1.5.	Eiclidean generalized TSP in grid clusters (including issues of complexity and approximability, PTAS)	[676]
1.6.	Clustered orienteering problems	[103,569]
2.	Solving approaches:	
2.1.	Solving the clustered TSP using the Lin-Kernighan-Helsgaun algorithm	[574]
2.2.	Approximation algorithms for not necessarily disjoint clustered TSP	[537]
2.3.	Approximation algorithms with bounded performance guarantees for clustered TSP	[536]
2.4.	GA for the clustered TSP	[1023]
2.5.	GA for the clustered TSP with a prespecified order on the clusters	[1024]
2.6.	New hybrid heuristic algorithm for clustered TSP	[891]
2.7.	Optimization of TSP using affinity propagation clustering and GA	[425]
2.8.	Heuristic and exact algorithms for clustered orienteering problem	[103]
2.9.	Effective multi-level memetic search with neighborhood reduction for the clustered team orienteering problem	[569]
3.	Applications of clustered TSPs:	
3.1.	Applications of the clustered TSP	[749]

A numerical example of clustered TSP is depicted in Fig. 2.24. Here the graph is divided into 7 clusters (without intersections): X_1, X_2, X_3, X_4, X_5, X_6, X_7.

A numerical example of orienteering problem (selection of a node in each cluster and designing a minimal route over the selected nodes) is depicted in Fig. 2.25. Here the close graph is divided into 8 clusters (without intersections): X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8.

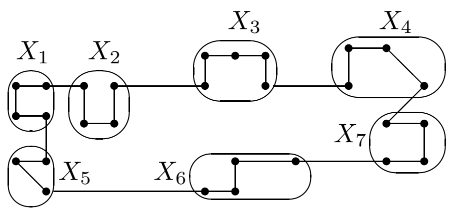


Fig. 2.24. Illustration for clustered TSP

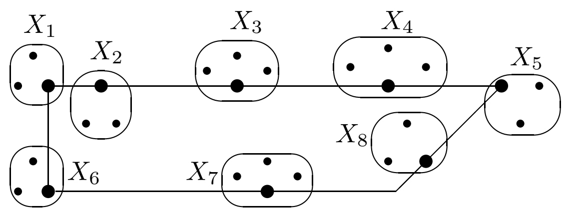


Fig. 2.25. Illustration for orienteering problem

2.1.15. Multidimensional scaling

The goal of multidimensional scaling is to find a low dimensional representation of a group of objects (e.g., sensor positions), such that the distances between objects fit as well as possible a given set of measured pairwise dissimilarities that indicate how dissimilar objects are (e.g., inter-sensor RSS). Some basic studies are pointed out in Table 2.23 (e.g., [222,350,371,725,1086,1153,1225]). It is prospective to use multidimensional scaling for various problems in communications as well.

Table 2.23. Multidimensional scaling

No.	Approach	Source(s)
1.	Basic approaches:	
1.1.	Classical multidimensional scaling	[1225]
1.2.	Metric multidimensional scaling	[222,350]
1.3.	Weighted multidimensional scaling	[282]
1.4.	Non-metric multidimensional scaling	[723,724]
1.5.	Generalized multidimensional scaling	[242,960]
1.6.	Generalized non-metric multidimensional scaling	[24]
1.7.	Statistical approaches to multidimensional scaling	[1054]
1.8.	Probabilistic multidimensional scaling	[1421]
1.9.	Two-way multidimensional scaling (review)	[467]
1.10.	Dynamic multidimensional scaling	[353]
2.	Some special studies:	
2.1.	Multidimensional scaling with restriction on the configuration	[758]
2.2.	New formulation of the nonmetric strain problem in multidimensional scaling	[1229]
2.3.	Global optimization in least-squares multidimensional scaling by distance smoothing	[515]
2.4.	Connection between kernel PCA and metric multidimensional scaling	[1295]
2.5.	Distributed weighted-multidimensional scaling	[349,409]
2.6.	Distributed on-line multidimensional scaling	[920]
2.7.	Multidimensional scaling with ranking (using AHP)	[593]
2.8.	Cluster-based multidimensional scaling	[1085]
2.9.	Multidimensional scaling-based localization techniques (WSNs, IoT)	[1087]

2.2. Some systems combinatorial clustering problems/frameworks

2.2.1. Hierarchical clustering

This hierarchical clustering is a basic well-known procedure for an initial set of elements (objects). For example, the hierarchical bottom-up aggregative clustering is a simple procedure to construct clustering solution by using the element proximity/distance (or similarity/dissimilarity) (e.g., [623–625,764–766, 769]). Some studies on hierarchical clustering are listed in Table 2.24.

Table 2.24. Some studies on hierarchical clustering

No.	Study	Source(s)
1.	General studies, surveys:	
1.1.	Hierarchical clustering problems and methods	[440,623–625]
1.2.	Numerical taxonomy	[1176,1177]
1.3.	Analysis of agglomerative clustering	[18]
1.4.	Hierarchical clustering schemes	[643]
1.5.	Surveys on hierarchical clustering algorithms and the recent developments	[931,1056]
1.6.	Theoretical analysis of hierarchical clustering	[516]
2.	Optimization approaches:	
2.1.	Combinatorial optimization and hierarchical classification	[174]
2.2.	Combinatorial scheme of hierarchical clustering	[764–767,769]
2.3.	Objective functions and algorithms for hierarchical clustering	[339]
2.3.	Hierarchical grouping to optimize an objective function	[1290]
2.4.	Online hierarchical algorithm for extreme clustering	[705]
2.5.	Particle-swarm optimization (PSO) based multi-view hierarchical clustering	[1413]
3.	Approximation approaches:	
3.1.	Approximate hierarchical clustering (via sparsest cut and spreading metrics)	[292]
3.2.	General approach for incremental approximation and hierarchical clustering	[815]
3.3.	Improved approximation algorithm for hierarchical clustering	[913]
3.4.	Subquadratic high-dimensional hierarchical clustering (γ-approximate Ward's algorithm, γ-approximate average-linkage algorithm)	[8]
4.	Evaluation approaches to hierarchical clustering:	
4.1.	Hierarchy cost of hierarchical clustering	[211]
4.2.	The price of hierarchical clustering	[123]
4.3.	Performance guarantees for hierarchical clustering	[367]
4.4.	Metrics for hierarchical clustering	[705,822,912]
5.	Multi-view hierarchical clustering:	
5.1.	Hierarchical ensemble framework for multi-view clustering	[478]
5.2.	Multi-view hierarchical clustering (without parameter selection)	[1402]
5.3.	Contrastive multi-view hyperbolic hierarchical clustering	[822]
5.4.	Hierarchical divisive clustering with multi-view point based similarity measure	[630]
5.5.	Multi-view adjacency constrained hierarchical clustering	[1332]
6.	Special studies:	
6.1.	Hierarchical clustering with structural constraints	[298]
6.2.	Stochastic multi-criteria divisive hierarchical clustering algorithm	[612]
6.3.	Mathematical morphology based method for hierarchical clustering	[1351]
6.4.	Adaptive grid-based forest-like clustering algorithm	[325]
6.5.	Contrastive hierarchical clustering	[1422]
6.6.	Information theory based hierarchical divisive clustering algorithm for categorical data	[1035]
6.7.	Gradient-based hierarchical clustering using continuous representations of trees in hyperbolic space	[912]
6.8.	Multi-objective hierarchical clustering (for tool assignment/allocation)	[366]
6.9.	Stochastic multi-criteria divisive hierarchical clustering algorithm	[612]
6.10.	Hierarchical clustering of message flows in multicast data dissemination system (optimization algorithm)	[1220]
6.11.	Computational complexity of hierarchical clustering (for community detection)	[249]

The hierarchical bottom-up aggregative clustering scheme consists in the series selection of the most closed element (object) pair and their aggregation (condensing). Evidently, the algorithmic complexity of the procedure corresponds the number of element pairs (i.e., $O(n^2)$).

Here, a special node-condensing (node-aggregative) clustering procedure can be considered as an extension of the hierarchical clustering:

Stage 1. Selection of a set of elements as centers $H = \{h_1, ..., h_i, ..., h_k\}$, $h_i \in A$ $\forall i = \overline{1,k}$ (for condensing, analogues of the forest root nodes).

Stage 2. For each $h_i \in H$: aggregation of elements which are close to the selected h_i to form the cluster (i.e, by constraints for the cluster as cluster size, etc.).

Stage 3. Deletion of the obtained cluster elements from initial element set A. If the the rest element set is empty then Stage 4. otherwise Go To Stage 1.

Stage 4. Stop.

A simlified illustrative numerical example of hierarchical (agglomerative, bottom-up) clustering algorithm (for 9 initial items) is shown in Fig. 2.26 (e.g., [764–767,769]). Here at each stage two the most close items are integrated. The clustering solution can be considered at stage 5, at stage 6, or at stage 7.

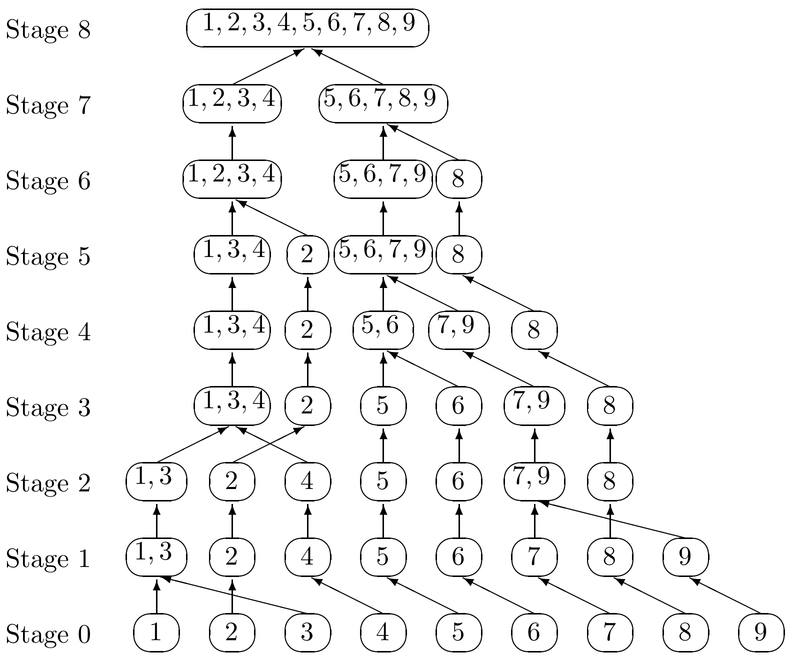


Fig. 2.26. Illustrative example of hierarchical clustering

2.2.2. Balanced clustering

Recently, the significance of balanced clustering problems has been increased. Some basic types of balanced clustering are examined in the authors publications [771–774,777,778]. In general, the following basic balance requirements (i.e., requirements to balanced components of the clustering solutions) are used: (a) balance requirements to cluster sizes (e.g., [238,482,583,712,766,769,823,890,1414]), an illustrative example is depicted in Fig. 2.27 (each cluster contains 4 items); (b) structured balance requirements to cluster element type structures (in case of clustering of multi-type items) (e.g., [771,772]), an illustrative example is depicted in Fig. 2.28 (each cluster has the following element type structure: one item of type 1, two items of type 2, two items of type 3).

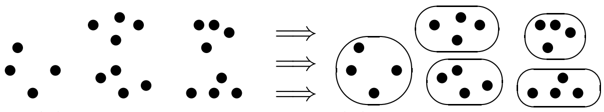
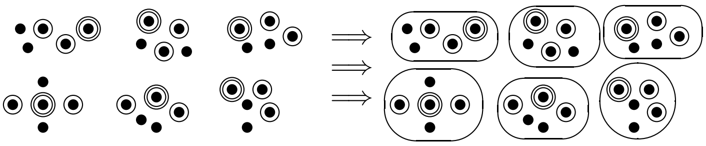

(a) initial items (b) balanced clustering

Fig. 2.27. Balanced clustering (by cluster sizes)



(a) initial items (b) balanced clustering

Fig. 2.28. Balancing by structure of cluster item types

Some combinatorial balanced clustering studies (including balanced set partitioning, balanced graph partitioning, dynamic balanced clustering) are pointed out in Table 2.25.

Table 2.25. Some balanced clustering studies

No.	Study	Source(s)
1.	Balanced clustering with cluster size constraints:	
1.1.	Balanced graph partitioning into balanced components	[98,149,191,200,253] [439,455,716]
1.2.	Generating clusters of similar sizes by constrained balanced clustering (τ-balanced clustering methods)	[823]
1.3.	Balanced k-means clustering	[288,865]
1.4.	Optimizing mean squared error for clustering with balanced size constraints	[1205]
2.	k-balanced clustering/partitioning:	
2.1.	k-balanced partitioning problem (partition of set into k balanced subsets)	[456]
2.2.	Multiply balanced k-partitioning	[90]
2.3.	Weight-balanced clustering (partitioning into k weight-balanced subsets)	[224,225,238]
2.4.	Balanced partition problems (partition of set into balanced subsets)	[482,583,712,890]
3.	Soft, hard and strong balanced clustering:	
3.1.	Model-based clustering with soft balancing	[1404]
3.2.	Soft and hard hybrid balanced clustering with innovative qualitative approach	[96]
3.3.	Strong balance-constrained clustering or hard-strong clustering	[97]
4.	Some special balanced clustering:	
4.1.	Balanced clustering: a uniform model and fast algorithm	[820]
4.2.	Balanced clustering based on collaborative neurodynamic optimization	[358]
5.	Balanced clustering under structures:	
5.1.	Partitioning (hierarchically clustered) complex networks via size-constrained graph clustering	[766,769,893]
5.2.	Balanced clustering with tree-like structures over clusters	[777]
5.3.	Combinatorial balanced clustering and partitioning (survey) (including set partitioning, graph partitioning, balancing by cluster element type structure)	[771,772]
6.	Dynamic and online balanced clustering:	
6.1.	Online balanced clustering (analysis)	[205]
6.2.	Dynamic load balanced clustering problem in mobile ad hoc networks (GA)	[322]
6.3.	Streaming balanced clustering	[432]

2.2.3. Multi-attribute/multiobjective clustering

In recent years, multicriteria (i.e., multiobjective, multi-attribute) clustering schemes are widely used when the items are evaluated by vector estimates. Here the following approaches are used: (i) multicriteria methods for selection at local and/or global levels, (ii) Pareto-efficient solutions, and (iii) special item distances/proximities (e.g., multiple distance measures between items). Various quality criteria for evaluation of the clustering solutions can be examined as well. Some studies on multicriteria/multiobjective (multi-attribute) clustering are listed in Table 2.26.

Table 2.26. Some multiobjective (multi-attribute) clustering studies

No.	Study	Source(s)
1.	Basic multiobjective approaches:	
1.1.	Direct multicriteria clustering algorithms	[457]
1.2.	Formalizing and solving the problem of clustering in MCDA	[880]
1.3.	Method for clustering in WSNs via TOPSIS multicriteria decision-making algorithm	[1147]
1.4.	Energy efficient multi-attribute based clustering scheme for energy harvesting WSNs	[1237]
1.5.	Multi-attribute, multi-weight clustering approach	[1109]
1.6.	Data-driven iterative multi-attribute clustering algorithm	[153]
1.7.	Multi-attribute subspace clustering (via weighted tensor nuclear norm minimization)	[529]
1.8.	Multi-objective clustering ensemble approach for crowdsourced clustering	[297]
1.9.	Multicriteria clustering approach (similarity indices, clustering ensemble techniques)	[1081]
1.10.	Multi-objective weighted clustering for remote monitoring system in WSN (optimization)	[1216]
2.	Multiobjective k-means clustering approaches:	
2.1.	Extension of the k-means algorithm for multiobjective clustering	[373]
2.2.	Integrating multi-objective optimization with weighted k-means for clustering	[981]
2.3.	Multiattribute SOM-K-Means clustering	[1420]
3.	Evolutionary multiobjective approaches:	
3.1.	Multiobjective genetic algorithms for clustering	[879]
3.2.	Evolutionary multi-objective clustering approaches	[553,919,928]
3.3.	General multiobjective clustering approach based on multiple distance measures	[840]
3.4.	Co-evolutionary multi-objective approach for a k-adaptive graph-based clustering	[887]
3.5.	Evolutionary multi-objective clustering over multiple conflicting data views	[484]
3.6.	Evolutionary many-objective approach to multiview clustering (using feature and relational data)	[646]
3.7.	Multi-objective clustering (kernel based approach using Differential Evolution)	[948]
3.8.	Multi-objective clustering ensemble (extended Pareto-based multi-objective GA)	[442]
4.	Combinatorial multiobjective clustering:	
4.1.	Multiobjective clustering with metaheuristic (some current trends and methods)	[217]
4.2.	Multiobjective clustering using particle swarm optimization (PSO)	[121,506]
4.3.	Multi-objective particle swarm and simulated annealing algorithm	[16]
4.4.	Multi-attribute hierarchical clustering	[318,764]
4.5.	Multiobjective simulated annealing for fuzzy clustering (with stability and validity)	[161]
4.6.	Approaches to multicriteria clustering (brief survey including various criteria, etc.)	[766,769]
4.7.	Multi-objective hierarchical clustering for tool assignment/allocation	[366]
4.8.	Exact algorithm for the multicriteria ordered clustering problem (elicitation of ordered groups of alternatives in multicriteria context)	[375]
4.9.	Partially ordered clustering in multicriteria comparative context	[1079]
5.	Multi-objective clustering based on game theory:	
5.1.	Autmatic multi-objective clustering based on game theory	[573]
5.2.	Enriched game-theory k-means technique for multi-objective clustering	[147]
6.	Multiobjective clustering under uncertainty:	
6.1.	Multiobjective spatial fuzzy clustering algorithm	[1391]
6.2.	Multi-objective technique for differential fuzzy clustering	[1089]
6.3.	Multi-objective genetic algorithm with fuzzy c-means for automatic clustering	[1294]
6.4.	Multiobjective simulated annealing for fuzzy clustering (with stability and validity)	[161]
6.5.	Stochastic multi-criteria divisive hierarchical clustering algorithm	[612]
7.	Frameworks/systems/tools for multi-objective clsutering:	
7.1.	Framework for multi-objective clustering (application to co-location mining)	[639]
7.2.	Collaborative DSS for multi-criteria automatic clustering (DEA&Best-Worst-Method)	[621]
7.3.	Enriched game-theoretic framework for multi-objective clustering	[147]
7.4.	Interactive framework for robust multicriteria clustering (propject portfolio analysis)	[654]
7.5.	Hierarchical multiple criteria ordered clustering approach as a contemporary tool for sorting and ranking problems	[393]

2.2.4. Consensus clustering (aggregation clustering)

The problem of consensus clustering (cluster ensemble, aggregation clustering) is examined as the following [410,498,1311]. There is an initial set of items and a preliminary defined (or pre-designed)

n partitions of the item set (as n clustering solutions) (Fig. 2.29). The problem consists in finding an aggregated clustering (consensus/agreement) solution that is close to the above-mentioned n initial clustering solutions. The problem belongs to class of NP-hard problems (e.g., [410,1311]).

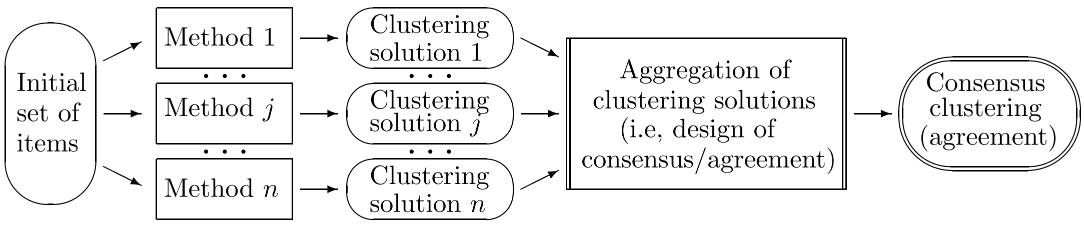


Fig. 2.29. Illustration of consensus (aggregation) clustering

Some consensus clustering (cluster ensemble, aggregation clustering) studies are listed in Table 2.27.

Table 2.27. Some consensus clustering (cluster ensemble, aggregation clustering) studies, part 1

No.	Study	Source(s)
1.	General (survey, problem, comparison study):	
1.1.	Review on consensus clustering methods (unsupervised consensus learning techniques, exact, approximation, and heuristic approaches)	[1311]
1.2.	Clustering aggregation (correlation clustering, clustering categorical data)	[498]
1.3.	Consensus clustering algorithms: comparison and refinement	[501]
1.4.	Clustering ensembles: models of consensus and weal partitions	[1223]
1.5.	Heterogeneous data integration with consensus clustering formalism	[464]
1.6.	K-means-based consensus clustering (unified view)	[1306]
1.7.	Aggregation of clustering solutions	[766,767]
1.8.	Consensus clustering in complex networks	[747]
1.9.	From clustering to clustering ensemble selection (review)	[502]
1.10.	Survey of approaches for cluster ensembles (extensions and applications)	[221]
2.	Solving approaches:	
2.1.	Construction of an optimal consensus clustering from multiple clusterings	[199]
2.2.	Randomized PTAS for the minimum Consensus Clustering with a fixed number of clusters	[219]
2.3.	Multiview consensus graph clustering	[1366]
2.4.	Fast Consensus Clustering via local optimization with dynamic similarity updates	[500]
2.5.	Weighted framework for unsupervised ensemble learning based on internal quality measures	[1241]
2.6.	K-means based consensus clustering (unified view, algorithms, applications)	[838,1273]
2.7.	Combining multiple clusterings using evidence accumulation	[468]
2.8.	Weighted consensus clustering – integration of clustering methods (application to Big Data, usage for group decision making)	[72]
2.9.	Cliques based method for combining multiple clustering (CLICOM)	[897]
2.10.	Survey of clustering ensemble algorihtms (cluster ensemble, consensus partition)	[1246]
2.11.	Cluster ensemble selection and consensus clustering (multi-objective optimization approach)	[55]
2.12.	Multi-level consensus function clustering ensemble	[1016]
2.13.	Clustering ensemble method (K-means, machine learning)	[84]
2.14.	Cumulative voting consensus method for partitions with variable number of clusters (consensus clustering voting method with linear computational complexity)	[140]
2.15.	Approximate clustering ensemble method for big data (distributed computing framework)	[860]
2.16.	Robust ensemble clustering using probability trajectories	[595]
2.17.	Meta-cluster based consensus clustering with local weighting and random walking	[564]

Table 2.27. Some consensus clustering (cluster ensemble, aggregation clustering) studies, part 2

No.	Study	Source(s)
3.	Consensus/ensemble clustering under uncertainty (fuzzy clustering, soft clustering):	
3.1.	Consensus-driven fuzzy clustering	[1003]
3.2.	Ensemble clustering with fuzzy approach	[136]
3.3.	Combination scheme for fuzzy clustering	[396]
3.4.	Fuzzy consensus clustering with applications on big data	[1307]
3.5.	Consnesus-based ensembles of soft clustering	[1029]
3.6.	Scalable incremental fuzzy consensus clustering algorithms for handling big data	[635]
3.7.	Large-scale consensus fuzzy clustering (for handling big data)	[576]
3.8.	Fuzzy ensemble clustering based on self-coassociation and prototype propagation	[804]
3.9.	Multi-view fuzzy consensus clustering model (for malware threat attribution)	[542]
3.10.	Consensus measure-based three-way clustering method for fuzzy large group decision making	[530]
4.	Solving frameworks:	
4.1.	Clustering ensemble framework based on elite selection of weighted clusters	[994]
4.2.	Knowledge reuse framework for combining multiple partitions (cluster ensembles)	[1191]
4.3.	Scalable framework for cluster ensemble	[582]
4.4.	Flexible iterative framework for consensus clustering	[892]
4.5.	Theoretic framework of K-means-based consensus clustering	[1303]
4.6.	Multiple consensus clustering framework	[800]
5.	Issues of complexity and effectiveness:	
5.1.	Consensus clustering problems are NP-hard	[410,1311]
5.2.	Parameterized complexity of consensus clustering	[410]
5.3.	Effectiveness of the least squares consensus clustering	[902]

2.2.5. Dynamic and online clustering

The significance of dynamic and online clustering has been increased (e.g., [65,322,770,812,1384]). An illustration of this clustering type is depicted in Fig. 2.30.

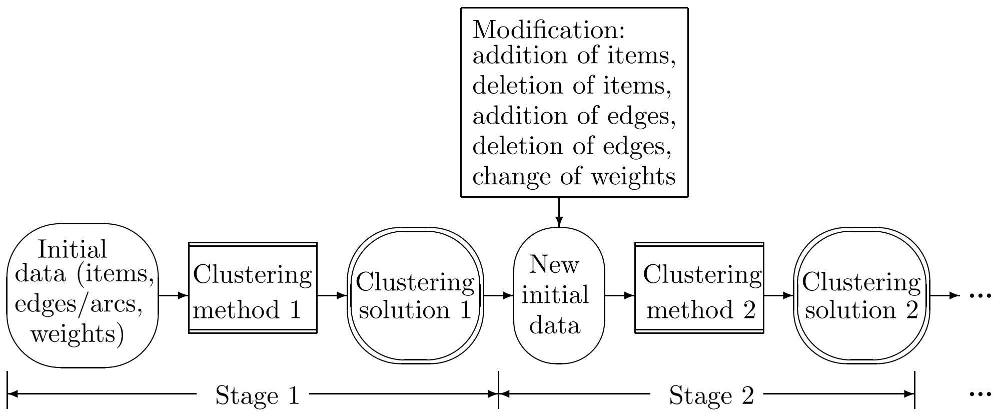


Fig. 2.30. Illustration of dynamic/online clustering

These problems are applied in communication systems (e.g., dynamic network topology management, network facility location and relocation, network reconfiguration, data streams management, dynamic load balancing). Some dynamic clustering studies are pointed out in Table 2.28. Some online clustering studies are pointed out in Table 2.29.

Note the problems of restructuring in clustering of dynamic combinatorial clustering (as one-stage restructuring, multistage restructuring, and cluster/element trajectories) are suggested and described in [766–770]. Here a set of problem criteria involves the cost of changes for clustering solutions at each transformation stage (in addition to quality of the clustering solutions).

Table 2.28. Some dynamic clustering studies

No.	Study	Source(s)
1.	Some basic dynamic clustering studies:	
1.1.	Survey on dynamic combinatorial clustering	[770]
1.2.	Dynamic clustering using combinatorial particle swarm optimization	[877]
1.3.	Combination of K-means and PSO for dynamic clustering	[659]
1.4.	Dynamic clustering and resource allocation algorithm for downlink CoMP systems	[168]
1.5.	Dynamic clustering approach in wireless networks with multi-cell cooperative processing	[991]
1.6.	Dynamic clustering for multi-user distributed antenna system	[828]
1.7.	Dynamic user-centric clustering for uplink cooperation in multi-cell wireless networks	[1384]
1.8.	Joint scheduling and dynamic clustering in downlink cellular networks	[505]
1.9.	Dynamic joint clustering scheduling for downlink CoMP systems with limited CSI	[167]
1.10.	Dynamic clustering of base stations for future wireless networks	[992]
1.11.	Dynamic clustering of mobile network with allocation of mobile access points	[175]
1.12.	Dynamic clustering for reconfiguration of backbone for WSNs	[177]
1.13.	Data similarity aware dynamic node clustering (WSNs)	[496]
1.14.	Dynamic image clustering/classification (particle swarm optimization)	[971,978]
1.15.	Dynamic clustering approach using multi-verse optimizer for Fog-assisted IoT devices	[116]
1.16.	Dynamic clustering for reconfiguration of backbone for WSN	[177]
2.	Dynamic load balanced clustering:	
2.1.	Dynamic load-balanced clustering in ad hoc networks (hybrid ant colony optimization)	[579]
2.2.	Energy efficient load-based clustering method for mobile WSNs	[65]
2.3.	Dynamic load balanced clustering problem in mobile ad hoc networks (dynamic GAs)	[322]

Table 2.29. Some online clustering studies

No.	Study	Source(s)
1.	Surveys on online clustering:	
1.1.	Survey on real-time clustering of data streams	[1423]
1.2.	Survey on data streams clustering (including online clustering)	[1165]
1.3.	On-line clustering (three methods)	[229]
1.4.	Online clustering algorithms	[172]
1.5.	Review on clustering techniques (creating better user experience for online roadshow)	[812]
1.6.	Analysis of online balanced clustering	[205]
2.	Online clustering based on k-means approaches:	
2.1.	Algorithm for online k-means clustering	[810]
2.2.	Efficient online spherical k-means clustering	[1403]
2.3.	Online constrained K-means clustering	[1033]
2.4.	Online k-means clustering of nonstationary data	[697]
2.5.	Dynamic online k-means	[33]
3.	AI-based approaches (e.g., machine learning, neural networks) for online clustering:	
3.1.	Reinforcement learning approach to online clustering	[811]
3.2.	Online deep clustering for unsupervised representation learning	[1367]
3.3.	Twin contrastive learning for online clustering	[803]
3.4.	Data stream fuzzy clustering and its online learning	[215]
4.	Special approaches for online clustering:	
4.1.	LINKS: a high-dimensional online clustering method	[872]
4.2.	Revisiting Gaussian neurons for online clustering with unknown number of clusters	[422]
4.3.	Kernel-based algorithm for online clustering	[227]
4.4.	Federated online clustering of bandits	[844]
4.5.	Online clustering with experts	[332]
4.6.	Semantic, hierarchical, online clustering for web search results	[1369]
4.7.	Online hierarchical algorithm for extreme clustering	[705]
5.	Online clustering of data streams, trajectory clustering:	
5.1.	Online clustering of parallel data streams	[197]
5.2.	On-line trajectory clustering for anomalous events detection	[1017]
5.3.	Online clustering of processes (novel non-parametric online clustering algorithm for time-series data)	[677]
5.4.	Online clustering of evolving data streams	[606,615]
5.5.	Online semantic-enhanced Dirichlet model for short text stream clustering	[736]
5.6.	Online clustering of evolving data streams using a density grid-based method	[1208]

2.2.6. Unequal clustering

In recent years unequal clustering problems are often used in communication systems (e.g., [144,170, 881,1256]). An illustration example of unequal clustering is shown in Fig. 2.31. A special example of an unequal hierarchical clustering structure for cluster formation in WSNs is depicted in Fig. 2.32. (based on [1256], small clusters are near base station).

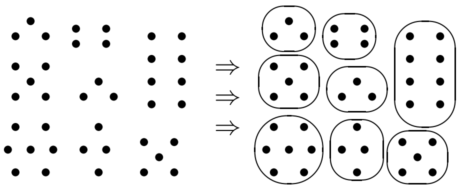


Fig. 2.31. Example of unequal clustering

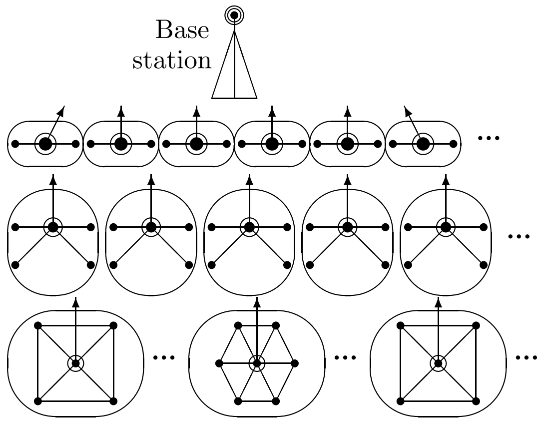


Fig. 2.32. Unequal hierarchical clustering

Some unequal clustering studies are pointed out in Table 2.30.

Table 2.30. Some unequal clustering studies

No.	Study	Source(s)
1.	Some approaches for unequal clustering:	
1.1.	Coverage-aware unequal clustering algorithm for wireless sensor networks	[881]
1.2.	Unequal clustering algorithm for WSN based on fuzzy logic and improved ACO	[1180]
1.3.	Energy aware fuzzy approach to unequal clustering in WSNs	[150]
1.4.	Energy based cluster head selection unequal clustering algorithm with dual sink	[66]
2.	Some applications of unequal clustering:	
2.1.	Unequal clustering for maximizing lifetime of WSNs	[144]
2.2.	Unequal cluster based routing protocol in WSNs	[312,1416]
2.3.	Unequal clustering in WSNs for distributed load balancing (fuzzy approach)	[170]
2.4.	Unequal clustering to construct multilayer network (cluster-based distributed routing protocol for WSNs)	[1256]
2.5.	Unequal clustering cross-layer protocol for WSNs	[474]
2.6.	Energy aware distributed unequal clustering protocol for heterogeneous WSNs	[534]
2.7.	Fuzzy-based multi-hop unequal cluster routing (SDN, WSN)	[851]
2.8.	Energy-efficient cluster-based routing protocol using unequal clustering and improved ant colony optimization for WSNs	[923]
2.9.	Energy and spectrum aware unequal clustering in cognitive radio sensor networks (with deep learning based primary user classification)	[1188]
2.10.	Optimizing energy consumption in WSN-based IoT using unequal clustering	[11]

2.2.7. Trajectory clustering and clustering time series data (streams)

In recent years, the significance of trajectory clustering and clustering of time series data (streams) has been increased (e.g., in dynamical systems, in various systems with moving objects, in multi-target tracking systems).

Some trajectory analysis/clustering studies are pointed out in Table 2.31.

Table 2.31. Some trajectory analysis/clustering studies time series data (streams) clustering

No.	Study	Source(s)
1.	Surveys:	
1.1.	Trajectory clustering analysis (survey)	[203]
1.2.	Review of moving object trajectory clustering algorithms	[1356]
1.3.	Clustering data streams	[520]
1.4.	Trajectory data mining (overview)	[1401]
1.5.	Trajectory indexing and retrieval	[387]
1.6.	Deep learning for time series classification (review)	[450]
1.7.	Clustering massive data streams (summarization paradigm)	[30]
1.8.	Survey on data streams clustering (including online clustering)	[1165]
1.9.	Survey on clustering data streams	[520]
2.	Studies and methods for trajectory clustering:	
2.1.	Clustering uncertain trajectories	[1004,1005]
2.2.	Trajectory similarity clustering based on multi-feature distance measurement	[1350]
2.3.	Temporal-constrained sub-trajectory cluster analysis	[1006]
2.4.	Integrating graph partitioning and matching for trajectory analysis	[816]
2.5.	Unsupervised trajectory clustering via adaptive multi-kernel-based shrinkage	[1317]
2.6.	Incremental clustering for trajectories	[590,791]
2.7.	Integral invariants for effective 3D motion trajectory matching and recognition	[1138]
2.8.	Trajectory learning for activity understanding: unsupervised, multilevel, and long-term adaptive approach	[921]
2.9.	Trajectory clustering: a partition-and-group framework	[753]
2.10.	Trajectory space (dual representation for nonrigid structure from motion)	[52]
2.11.	Vector field k-means: clustering trajectories by fitting multiple fields	[460]
2.12.	Novel trajectory clustering technique based on multi-view similarity	[1249]
2.13.	Spatio-temporal feature trajectory clustering based on deep learning	[568]
2.14.	Rapid trajectory clustering based on neighbor spatial analysis	[1034]
2.15.	Hierarchical trajectory clustering for spatio-temporal periodic pattern mining	[1370]
3.	Clustering of time series data (streams):	
3.1.	Clustering distributed time series in sensor networks	[1340]
3.2.	Incremental clustering of dynamic data streams using connectivity based representative points	[853]
3.3.	Real-time clustering of data streams	[1423]
3.4.	Incremental clustering on evolving data stream	[956]
3.5.	Density-based clustering over an evolving data stream with noise	[265]
3.6.	Synchronization-based clustering on evolving data stream	[1139]
3.7.	Density-based clustering of data streams at a multiple resolutions	[1262]
4.	Some applied studies:	
4.1.	Visual cluster analysis of trajectory data with interactive Kohonen maps	[1108]
4.2.	Interactive visual clustering of large collections of trajectories	[99]
4.2.	Graph-based approach to vehicle trajectory analysis	[524]
4.3.	3D human action recognition by shape analysis of motion trajectories	[390]
4.4.	Detection and classification of highway lanes using vehicle motion trajectories	[896]
4.5.	Efficient anomaly monitoring over moving object trajectory streams	[247]
4.6.	On-line trajectory clustering for anomalous events detection	[1017]
4.7.	Understanding sport activities from correspondences of clustered trajectories	[1235]
4.8.	Clustering of vehicle trajectories	[129]
4.9.	Syntactic matching of trajectories for ambient intelligence applications	[1018]
4.10.	Real-time motion trajectory indexing and retrieval of video sequences, object trajectory-based activity classification and recognition	[179,180]
4.11.	Learning semantic scene models by object classification and trajectory clustering	[1371]
4.12.	Efficient k-nearest-neighbor search algorithms for historical moving object trajectories	[476]
4.13.	Time-focused clustering of trajectories of moving objects	[942]
4.14.	Trajectory clustering and regionalization for ocean eddies (South China sea)	[906]
4.15.	Traclass: trajectory classification (hierarchical region-based&trajectory-based clustering)	[754]
4.16.	Trajectory clustering for mining multiple periodic patterns (oceanic trajectories)	[414]

3. Clustering schemes in communication networks

3.1. Categories

In recent two decades, several versions of taxonomies for basic clustering schemes for communication networks have been suggested (e.g., [376,1194,1250,1345]). In [1345] the following six basic clustering clustering schemes are pointed out: type 1: dominated set based clustering, type 2. low-maintenance clustering, type 3. mobility-aware clustering, type 4. energy-efficient clustering, type 5. load-balancing clustering, and type 6. combined-metrics-based clustering. An integrated set (categories) of basic clustering schemes in communication network is presented in Table 3.1.

Table 3.1. Some categories of basic clustering schemes in communications

No.	Scheme	Brief description	Source(s)
1.	Clustering for backbone optimization:		
1.1.	Connecting dominated set (DS) method	(i) selection of candidates for clusterheads, (ii) detection of redundant dominating nodes, (iii) design of connected k-hop DS	[964,1297]
1.2.	Weakly connecting dominated set method	Detection of a small weakly connected DS (to obtain non-overlapping clusters)	[305]
1.3.	Domatic partition in networks	Design of t disjoint dominating sets (maximizing t)	[452,482] [1348]
1.4.	Clustering for efficiently of the reconfigurable backbones of WSNs	(a) clique covering (clustering), (b) connection of selected nodes (CHs) (c) backbone reorganization (with new node(s), new cluster(s))	[177]
2.	Multi-hop clustering schemes:		
2.1.	Multi-hop clustering (MaxMin algorithm)	Heuristic to design a d-hop configuration	[91,964]
2.2.	Connected k-hop clustering (in Ad Hoc networks)	Design of connected k-hop clustering,	[964,1324]
2.3.	Multi-hop clustering in mobile ad-hoc networks	Based on neighborhood benchmark	[1336]
2.4.	Link- and hop-constrained clustering	Multi-hop WSNs	[316]
2.5.	Multi-hop clustering	Hierarchical distributed management, routing in WSNs	[118,1124]
3.	Clustering schemes for data aggregation:		
3.1.	Node clustering and data aggregation	Sailfish optimization method	[95]
3.2.	Data aggregation based on Energy efficiency optimization	usage of hybrid LEACH protocol	[683]
3.3.	Aggregation scheme in clustered WSN	Adaptation methods	[309]
3.4.	Secure statistical data aggregation	Heuristic angular clustering	[721]
3.5.	Reliable data aggregation scheme	Hybrid deep learning techniques	[1064]
4.	Energy efficient clustering:		
4.1.	Clustering scheme for ad hoc networks	Stable energy-efficient location	[910]
4.2.	Energy efficient clustering protocol	Particle swam optimization (PSO) method	[1067]
4.3.	Special energy efficient scheme (WSNs)	Unequal clustering algorithm	[1353]
5.	Cluster scheduling schemes:		
5.1.	Effective cluster scheduling scheme for WSNs	Local gravitation method	[1322]
5.2.	Hierarchical clustering-task scheduling in cluster-based WSNs	Hierarchical scheduling policy (HCSP)	[949,1013]
6.	Access-based clustering schemes:		
6.1.	Cluster-based channel assignment	Channel assignment in multilayer networks (e.g., IEEE 802.11 networks)	[497]
6.2.	Allocation of users into access points (in each predefined	Multicriteria assignment network cluster)	[767]

3.2. Clustering scheme for backbone optimization

The basic clustering-based scheme for backbone design is as follows (e.g., [177]):

Stage 1: clustering (e.g., clique covering).
Stage 2: selection/assignment of cluster heads.
Stage 3: design of backbone over cluster heads.

An illustrative example is presented Fig. 3.1:
(i) initial network (Fig. 3.1a): graph $G = (A, E)$, set of nodes $A = \{1, 2, ..., 21\}$;
(ii) clique clustering (Fig. 3.1b): cluster $X_1 = \{1, 2, 3, 4\}$, cluster $X_2 = \{5, 6, 7\}$, cluster $X_3 = \{8, 9, 10\}$, cluster $X_4 = \{11, 12, 13, 14\}$, cluster $X_5 = \{15, 16, 17, 18\}$, cluster $X_6 = \{19, 20, 21\}$;
(iii) set of cluster heads (Fig. 3.1c): cluster X_1: 4, cluster X_2: 7, cluster X_3: 10, cluster X_4: 12, cluster X_5: 16, cluster X_6: 19;
(iv) connected backbone (Fig. 3.1c): $B = \{12, 4, 16, 19, 10, 7\}$.

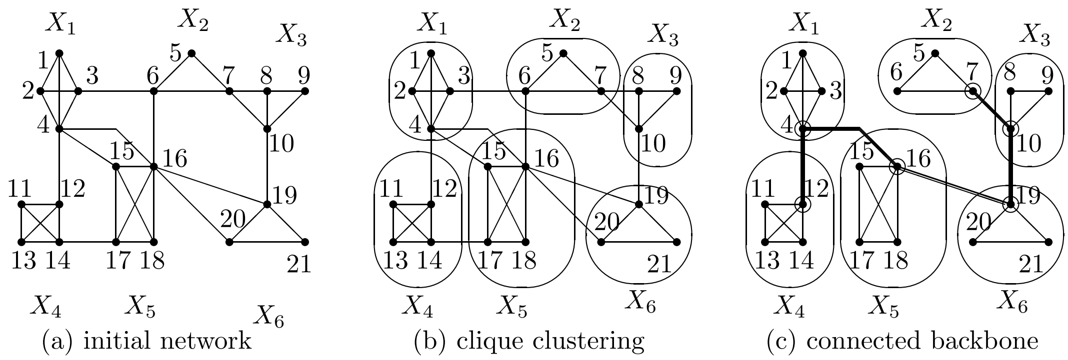


Fig. 3.1. Clustering based backbone design

The above-mentioned scheme is used as a basis for efficiently reconfigurable backbones in communication networks (e.g., for wireless sensor networks). In general several other backbone design schemes are used as well, for example: (i) scheme based on dominating set, (ii) scheme based on independent set, (iii) scheme based on maximum leafs spanning tree/forest, and (iv) scheme based on k-centers in network.

3.3. Clustering scheme for data aggregation

The clustering aggregation schemes are widely used in communication networks. Some clustering based studies for data aggregation are listed in Table 3.2.

Table 3.2. Clustering based approaches for data aggregation in communication networks

No.	Study	Source(s)
1.	Survey on data aggregation techniques in WSNs (including taxonomy of cluster-based protocols)	[391]
2.	Adaptive data aggregation scheme in clustered WSN	[309]
3.	Efficient data aggregation and routing in sensor networks	[306]
4.	Hybrid LEACH protocol (energy efficiency optimization in IoT networks) for data aggregation	[683]
5.	k-center clustering for data summarization	[104,699]
6.	Heuristic angular clustering framework for secure statistical data aggregation in sensor networks	[721]
7.	Reliable cluster based data aggregation scheme for IoT network using hybrid deep learning techniques	[1064]
8.	Energy efficient cluster head selection for data aggregation in wireless sensors	[1063]
9.	Node clustering and data aggregation in WSN using sailfish optimization	[95]
10.	Fuzzy logic-based two-level clustering for data aggregation in WSN	[449]
11.	Slepian-Wolf coding based clustering algorithm for data aggregation in WSNs	[1160,1397]
12.	Data density correlation degree clustering method for data aggregation in WSN	[1354]
13.	Cluster-based weighted compressive data aggregation in WSNs	[7]
14.	Bandwidth efficient cluster-based data aggregation for WSN	[873,1048]
15.	Network clustering for data summarization in network traffic monitoring	[581]
16.	Energy-efficient cluster-based data collection by UAV in robotic WSNs	[521,522]
17.	Data collection based on multiple mobile nodes for WSN (clustering approach)	[990]

3.4. Multi-hop/multi-level clustering schemes

Some multi-hop/multi-level clustering schemes/studies are listed in Table 3.3.

Table 3.3. Some multi-hop/multi-level clustering schemes

No.	Study	Source(s)
1.	Basic multi-hop clustering approaches:	
1.1.	Multi-hop clustering (MaxMin algorithm) (heuristic to design a d-hop configuration)	[91,964]
1.2.	Energy-efficient multi-level adaptive clustering routing for sensor networks	[1263]
1.3.	Evidence-efficient multihop clustering routing scheme for large-scale WSNs	[796]
1.4.	Energy optimization clustering scheme for multi-hop underwater acoustic cooperative sensor networks	[1352]
1.5.	Fault tolerant dynamic multi-hop clustering in sensor network	[1092]
1.6.	Energy constrained multihop clustering algorithm for WSN	[1142]
1.7.	Link- and hop-constrained clustering for multi-hop WSNs	[316]
2.	Special multi-hope clustering methods:	
2.1.	k-hop clustering scheme for the optimal common control channel assignment (for cognitive radio networks, minimum dominating set problem)	[1321]
2.2.	Connected k-hop clustering (in Ad Hoc networks): design of connected k-hop clustering	[1324]
2.3.	Three level heterogeneous clustering protocol for WSN	[1026]
2.4.	Cluster-based distributed medium access control protocol for multichannel and multihop mobile cognitive radio ad hoc networks	[1310]
2.5.	Fuzzy logic-based clustering algorithm for multi-hop WSNs	[1173]
2.6.	Clustering scheme for hierarchical control in multi-hop wireless networks (three-layer hierarchy)	[163]
3.	Multi-hop cluster-based routing approaches:	
3.1.	Multi-hop cluster-based routing protocols in WSNs (survey based on methodology)	[445]
3.2.	Multi-hop cluster based routing approach for WSNs	[118]
3.3.	Directional multi-hop clustering routing protocol for WSNs	[939]
3.4.	Multi-hop dynamic clustering routing protocol for WSN in IoT environment	[848]

3.5. Access-based clustering scheme

Access-based clustering are often targeted to clustering of end-users and their allocation to local network centers (e.g., access points). Access-based clustering schemes are often very important for last mile network organization. Some studies on access-based clustering schemes are pointed in Table 3.4.

Table 3.4. Some studies on access-based clustering schemes

No.	Study	Source(s)
1.	Cloudlets: clusters of virtualization servers integration of the cloudlets into the access network (heuristics for cloudlet location)	[277]
2.	Cluster-based channel assignment: channel assignment in multilayer networks (e.g., IEEE 802.11 networks)	[497]
3.	Clustering of end-users set (with access points APs as cluster heads) (multicriteria assignment of end users into access points)	[767]
4.	Quality-balanced user clustering schemes for non-orthogonal multiple access systems	[1230]

3.6. Clustering-based scheduling

Traditionally, clustering-based scheduling approach is used in multiprocessor systems, distributed computing processes [338,489,656,814]. The general problem consists in mapping the digraph over initial tasks upon multiprocessor architecture (Fig. 3.2). The task clustering solution provides the following: (a) decreasing the problem dimension and (b) decreasing communications among task clusters Thus, the heuristic scheduling approaches are based on preliminary clustering of tasks. In addition, two methods are often used: (a) priority based scheduling and (b) duplication-based scheduling.

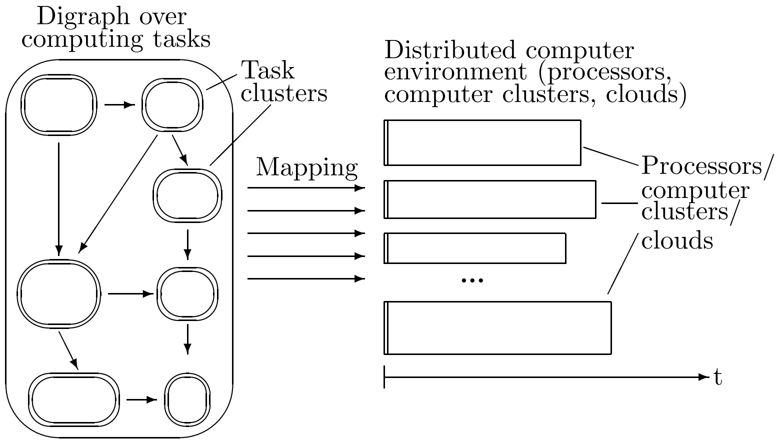


Fig. 3.2. Clustering-based scheduling in distributed computing

Evidently, this general situation corresponds to clustering of the computing tasks and clustering of the processing items. The general case is a basic one in communication network scheduling. Here a four-stage solving framework is considered for two sets: elements (i.e., tasks) and positions (processing units) (Fig. 3.3):

Stage 1. Clustering of *element* set (to decrease the dimension).

Stage 2. Clustering of *position* set (to decrease the dimension).

Stage 3. Mapping (assignment/allocation) of *element* clusters into *position* clusters. Clearly, several elements can be assigned to the same position.

Stage 4. Ordering of the allocated tasks for each *position* cluster.

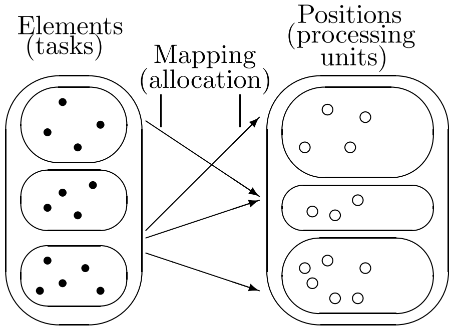


Fig. 3.3. Illustration for four-stage framework

Some studies in cluster-based scheduling are pointed out in Table 3.5.

Table 3.5. Some studies in cluster-based scheduling

No.	Study	Source(s)
1.	Clustering-based scheduling in multiprocessor systems, in distributed computing processes	[338,489,656,814]
2.	Hierarchical clustering-task scheduling policy (HCSP) in cluster-based WSNs	[949,1013]
3.	Time-interval balancing in multi-processor scheduling of composite modular jobs	[773]
4.	Scheduling sleeping nodes in high density cluster-based sensor networks	[385]
5.	Balanced-energy sleep scheduling scheme for high-density cluster-based sensor networks	[386]
6.	Serialized optimal relay schedules in two-tiered clustered WSNs	[985]
7.	Joint scheduling and dynamic clustering in downlink cellular networks	[505]
8.	Dynamic joint clustering scheduling for downlink CoMP systems with limited CSI	[167]
9.	Clustering-based scheduling for cognitive radio sensor networks	[608]
10.	Dynamic cluster scheduling for cluster–tree WSNs.	[1117]

3.7. Energy efficient clustering schemes

Energy efficient clustering schemes are widely used. Some studies are listed in Table 3.6.

Table 3.6. Some studies on energy efficient clustering schemes

No.	Study	Source(s)
1.	Energy efficient clustering:	
1.1.	Clustering algorithm for energy efficiency and safety in mobile, wireless and sensor networks	[355]
1.2.	Energy efficient clustering in WSNs using mobile sink	[1268]
1.3.	Energy efficient unequal clustering algorithm for WSNs	[1353]
1.4.	Stable energy-efficient location based clustering scheme for ad hoc networks	[910]
1.5.	Improved low-energy adaptive clustering hierarchy (LEACH) protocol in WSNs	[1385]
1.6.	BPA-CRP: a balanced power-aware clustering and routing protocol for WSNs (LEACH)	[364]
1.7.	PSO-based energy efficient clustering protocol in WSNs	[1067]
1.8.	Energy efficient fault tolerant clustering and routing algorithms for WSNs	[143]
1.9.	PSO-based approach for energy-efficient and energy-balanced routing and clustering in WSNs	[145]
1.10.	PSO based energy efficient clustering and sink mobility in heterogeneous WSNs	[1090]
1.11.	Centralized cluster-based approach via Grey Wolf optimizer for energy-efficient routing in WSN	[361]
1.12.	Energy aware clustering hierarchy protocol for large scale WSNs	[171]
1.13.	Energy-efficient chain-cluster based intelligent routing for WSNs	[1053]
1.14.	Hybrid LEACH protocol based on AI (energy efficiency optimization in IoT networks)	[683]
1.15.	Chaotic elite niche evolutionary algorithm for low power clustering in environment monitoring WSNs	[842]
2.	Energy efficient cluster head selection:	
2.1.	Modification of energy efficient unequal clustering mechanism (for cluster head selection)	[66]
2.2.	Energy-efficient cluster head selection in WSNs (improved Grey Wolf optimization algorithms)	[1070]
2.3.	PSO based energy efficient cluster head selection algorithm for WSNs	[1059]
2.4.	EA-CRP: a novel energy-aware clustering and routing protocol in WSNs (cluster head selection, multi-hop routing, multi-layer topology)	[362]
2.5.	Hybrid HSA nd PSO algorithm for energy efficient cluster head selection in WSN	[1136]
2.6.	MCH-EOR: multi-objective cluster head based energy-aware optimized routing in WSNs	[885]
2.7.	Energy efficient cluster head selection scheme in heterogeneous WSN	[1065]
2.8.	Grid-based CH selection (enhanced energy optimization routing protocol for WSNs)	[1072]
2.9.	Head selection for efficient data aggregation and routing in sensor networks (energy consumption)	[306]

4. On clustering in wireless and mobile networks

4.1. Clustering in WSNs

In general, the following types of WSNs are considered (e.g., [1125]): (i) terrestrial WSNs (e.g., [490]), (ii) underground WSNs (e.g., [53,58,1164]), (iii) underwater WSNs (e.g., [57,139,448,490]), (iv) multimedia WSNs (e.g., [3,59,80,146]), (v) mobile WSNs (e.g., [178,344,561]), (vi) wireless sensor and actuator networks (WSANs) (e.g., [56,1073,1316]), (vii) heterogeneous WSNs (e.g., [274]). Clustering is the basic approach for topology (i.e., network structure/architecture) management in WSNs (e.g., [682,1125,1126]). A simplified illustrative example of WSN hierarchical clustered topology is presented in Fig. 4.1. Here the following cluster deployment topology models are shown at the bottom layer:

(i) square model for cluster $X_{1,1}$,
(ii) hexagonal model for cluster X_{1,k_1},
(iii) pentagonal model for cluster $X_{n,1}$, and
(iv) 3×3 grid model for cluster X_{n,k_n}.

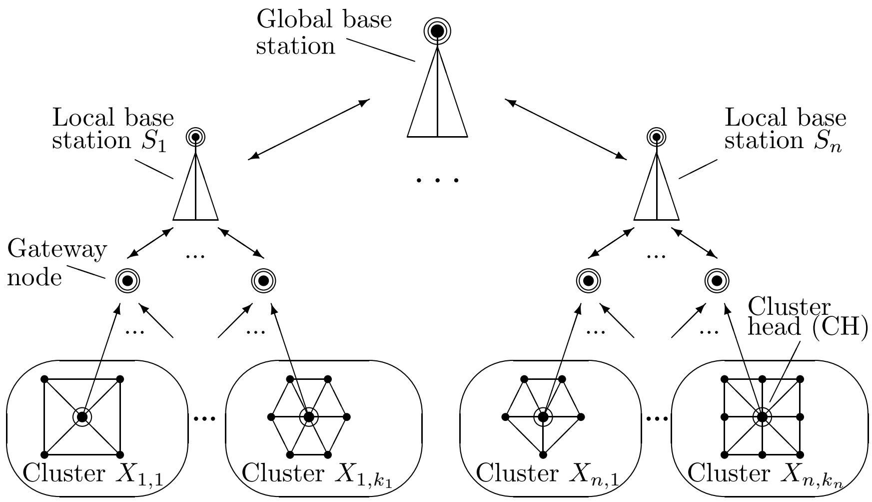


Fig. 4.1. Simplified example of WSN hierarchical clustered topology

Some survey on clustering in WSNs are pointed out in Table 4.1. Note the following basic clustering characteristics are considered in the clustering of WSNs: (i) cluster size, (ii) cluster density, (iii) intra-cluster characteristic, (iv) inter-cluster head connectivity, (v) number of clusters, (vi) stability characteristic, (vii) characteristic of cluster hierarchy (e.g., [428,649,1125,1126]). Some bibliography on studies in WSNs is pointed out in Table 4.2.

Table 4.1. Some survey on clustering in WSNs

No.	Study	Source(s)
1.	Clustering objectives in WSNs (survey and research direction analysis)	[1125]
2.	Survey and future directions on clustering in WSNs	[1126]
3.	Survey of clustering techniques in WSNs (including challenges in IoT scenarios)	[1319]
4.	Literature survey on clustering in WSNs (including: hierarchical architecture, clustering objectives, clustering characteristics, classification of clustering approaches)	[20]
5.	Review on clustering algorithms for WSNs	[979]
6.	Survey on optimization of clustering in WSN (techniques and protocols)	[649]
7.	Optimized clustering algorithms for large WSNs (review)	[1094]
8.	Graph theoretic clustering algorithms in MANETs and WSNs (survey)	[428]
9.	Survey on clustering algorithms for heterogeneous WSNs	[670]
10.	Survey on clustering techniques for cooperative wireless networks	[1194]
11.	Survey on clustering protocols in WSNs (classification, future directions)	[1066]
12.	Survey of energy-efficient clustering routing protocols for WSNs (metaheuristics)	[378]
13.	Aspects of clustering in WSNs (classical techniques, optimization, machine learning; review, taxonomy, research findings, challenges and future directions)	[94]

Table 4.2. Some studies on clustering in WSNs, part 1

No.	Study	Source(s)
2.	Basic studies (e.g., network clustering, cluster formation, cluster head selection):	
2.1.	Hierarchical (multi-level) clustering for WSNs, hierarchical network design	[162,745]
2.2.	Clusterhead (node) election/selection/location in WSNs	[78,102,142,254]
	(TOPSIS method)	[548,795]
2.3.	Cluster topology in WSN	[1098]
2.4.	Cluster formation in networks	[91,128]
2.5.	Clustering and routing for WSNs	[143,662,728,1170]
2.6.	Hierarchical cluster-based routing in WSNs	[601,1102,1120,1168]
2.7.	Node clustering in WSNs	[1344]
2.8.	Monitoring in cluster-based WSNs	[226]
2.9.	Energy-efficient clustering for heterogeneous WSNs	[633,731]
2.10.	EEMC: an energy-efficient multilevel clustering algorithm for large-scale WSNs	[641]
2.11.	Graph cut based clustering for cognitive radio ad hoc networks (without common control channels)	[1379]
2.12.	Cluster head selection using decision trees for WSNs	[37]
2.13.	Balanced clustering problem in large scale WSNs	[1226]
2.14.	Enhanced clustering and ACO-based multiple mobile sinks for efficiency improvement of WSNs	[719]
2.15.	Energy constraint clustering algorithms for WSNs (usage of dominating set)	[67]
2.16.	Optimal clustering for determining distributed antenna location (location of antenna units) in wireless networks	[1242]
3.	Clustering protocols for WSNs:	
3.1.	Distributed energy-efficient clustering protocol for WSNs	[280]
3.2.	SEECH: Scalable energy efficient clustering hierarchy protocol in WSNs	[1209]
3.3.	DHCR: energy-aware clustering protocol	[1084]
3.4.	EDIT: low cost clustering protocol	[1213]
3.5.	Distributed clustering protocol in WSNs using fuzzy logic	[1202]
3.6.	Energy-efficient multi-hop routing protocol based on grid clustering for WSNs	[596]
3.7.	Power efficient cluster-based routing for WSNs (honeybees swarm intelligence approach)	[115]
3.8.	Multi-hop cluster based routing approach for WSNs	[118,362]
3.9.	Hierarchical distributed management clustering protocol for WSNs	[1124]
3.10.	Evolutionary based application specific routing protocol for clustered WSNs	[1157]
3.11.	Memetic fuzzy clustering protocol for WSNs	[444]
3.12.	CRPD: a novel clustering routing protocol for dynamic WSNs	[1282]
3.13.	Novel efficient clustering protocol for energy harvesting in WSNs	[1088]
3.14.	Multi-hop dynamic clustering routing protocol for WSN in IoT environment	[848]
3.15.	Clustering protocol for pervasive WSN (blockchain enabled energy efficient red deep algorithm)	[957]
3.16.	Clustering based routing protocol for WSN implementing a mobile sink	[184]
3.17.	Clustering protocol for energy balance of WSN based on genetic clustering algorithm	[565]
3.18.	Directional multi-hop clustering routing protocol for WSNs	[939]
3.19.	Energy efficient protocol in WSN (optimized cluster head selection model)	[70]
3.20.	Energy efficient enhanced LEACH-C protocol in WSNs using cloud	[27]
3.21.	Energy-efficient heterogeneous ring clustering routing protocol for WSNs	[1381]
3.22.	Clustering based routing techniques in wireless body area networks	[1239]
3.23.	Clustered-based protocol for multi-hop heterogeneous WSNs (using comprehensive sensing)	[685]
3.24.	Hybrid LEACH protocol (energy efficiency optimization in IoT networks)	[683]
3.25.	Balanced parallel clustering protocol for WSNs (using K-means techniques)	[1203]
3.26.	Energy-balanced cluster-based protocol for WSNs	[1207]

Table 4.2. Some studies on clustering in WSNs, part 2

No.	Study	Source(s)
4.	Unequal clustering approach:	
4.1.	Unequal clustering for maximizing lifetime of WSNs	[144]
4.2.	Coverage-aware unequal clustering algorithm for WSNs	[881]
4.3.	Unequal clustering to construct multilayer network (cluster-based distributed routing protocol for WSNs)	[1256]
4.4.	Unequal clustering cross-layer protocol for WSNs	[474]
4.5.	Energy aware distributed unequal clustering protocol for heterogeneous WSNs	[534]
4.6.	Unequal cluster-based routing strategy in WSNs	[312]
4.7.	HEEC: a hybrid unequal energy efficient clustering for WSNs (including multi-hop routing, increasing network lifetime)	[233]
4.8.	Distributed load balancing unequal clustering in WSNs (fuzzy approach)	[170]
4.9.	Energy efficient routing protocol based on layers and unequal clusters in underwater WSNs	[1416]
4.10.	Energy hole problem based on unequal cluster-radius for WSNs	[829]
4.11.	Energy-balanced clustering in WSNs (unequal clustering)	[831]
4.12.	Unequal clustering algorithm for WSN (fuzzy logic and improved ACO)	[1180]
4.13.	Adaptive clustering based dynamic routing of WSNs via ant colony optimization	[1337]
4.14.	Hybrid unequal clustering for WSNs	[864]
4.15.	Load balancing fuzzy-based unequal clustering for WSNs assisted IoT	[34]
4.16.	Energy aware fuzzy approach to unequal clustering in WSNs	[150]
4.17.	Energy based cluster head selection unequal clustering with dual sink in WSNs	[66]
4.18.	Unequal clustering for optimizing energy consumption in WSN-based IoT	[11]
5.	Optimization approaches:	
5.1.	Particle swarm optimization based clustering algorithm with mobile sink for WSNs	[1278]
5.2.	Domatic partition in homogeneous WSNs (maximization of domatic number)	[452,482,1348]
5.3.	Multi-hop optimal clustering in hexagon and Voronoi cell structured WSNs	[735]
5.3.	Coverage-time optimization for clustered WSNs (power-balancing approach)	[1159]
5.5.	Multi-objective Cluster Head Based Energy-aware Optimized Routing algorithm on WSNs	[1102]
5.6.	Energy-aware clustering-based routing in wireless sensor networks using Cuckoo optimization algorithm	[675]
5.7.	PSO and artificial bee colony algorithm for clustering and mobile based software-defined WSNs	[1174]
5.8.	Cluster-based energy optimization algorithm in WSNs with mobile sink	[1261]
5.9.	Weight PSO and improved factor-based clustering algorithm for WSNs	[334]
5.10.	Multi-criterion optimization for energy efficient cluster formation in WSNs	[945]
5.11.	Efficient statistical clustering techniques for optimizing cluster size in WSNs	[418]
5.12.	Optimized clustering algorithms for large WSNs (review)	[1094]
5.13.	Optimized fuzzy clustering using moth-frame optimization in WSNs	[1218]
5.14.	Unconstrained optimization technique in WSNs for energy efficient clustering	[999]
5.15.	Hybrid optimization-based novel energy-efficient clustering for EH-WSNs	[1062]
5.16.	Optimal energy aware clustering in circular WSNs	[114]
5.17.	Optimized and load balanced clustering for WSNs (using MADM approaches)	[1050]
5.18.	Combinatorial optimization-based clustering algorithm for WSNs	[264]
5.19.	Energy-aware multilayer clustering-based butterfly optimization routing for underwater WSNs	[327]
5.20.	Energy-efficient clustering routing for WSNs based on energy consumption optimization	[598]
5.21.	Optimization based multi-objective weighted clustering for remote monitoring system in WSN	[1216]
5.22.	Multiple criteria clustering of mobile agents in WSN	[1169]
5.23.	Multi swarm optimization based clustering with tabu search in WSNs	[1195]
5.24.	Energy efficient clustering algorithm based on PSO for WSNs	[847]
5.25.	Optimization of clustering in WSN (techniques and protocols)	[649]
5.26.	Chaotic elite niche evolutionary algorithm for low power clustering in environment monitoring WSNs	[842]

Table 4.2. Some studies on clustering in WSNs, part 3

No.	Study	Source(s)
6.	Fuzzy clustering in WSNs:	
6.1.	Fuzzy clustering protocol for WSNs	[444]
6.2.	Sugeno fuzzy clustering algorithm for WSNs	[1158]
6.3.	Clustering mechanism based on Fuzzy-C means for WSNs	[1192]
6.4.	Fuzzy routing protocol for clustered WSNs	[1360]
6.5.	Distributed clustering protocol in WSNs using fuzzy logic	[1202]
6.6.	Fuzzy approach for unequal clustering in WSNs	[170]
6.7.	MOFCA: multi-objective fuzzy clustering algorithm for WSNs	[1116]
6.8.	HQCA–WSN: High-quality clustering for optimal cluster head selection in WSNs (using fuzzy logic)	[169]
6.9.	EHCR-FCM: energy efficient hierarchical clustering using fuzzy C-means for WSNs	[987]
6.10.	Optimized fuzzy clustering using moth-frame optimization in WSNs	[1218]
6.11.	Load balancing fuzzy-based unequal clustering for WSNs assisted IoT	[34]
6.12.	Energy aware fuzzy approach to unequal clustering in WSNs	[150]
6.13.	Fuzzy modelling based energy aware clustering in WSNs using modified invasive weed optimization (k-means, evolutionary technique, etc)	[1145]
6.14.	Fuzzy clustering for enhancing reliability and network lifetime of WSN	[750]
7.	Adaptive clustering approaches in WSNs:	
7.1.	PEACH: power-efficient and adaptive clustering hierarchy protocol for WSNs	[1338]
7.2.	Adaptive clustering for WSNs with a mobile sink	[1204]
7.3.	Improved three-layer low-energy adaptive clustering hierarchy for WSNs	[756]
7.4.	Adaptive clustering based dynamic routing of WSNs via ant colony optimization	[1337]
7.5.	Energy efficient adaptive clustering hierarchy approach for WSNs	[423]
7.6.	Energy-efficient adaptive clustering algorithm for	[1133]
7.7.	Agile adaptive clustering algorithm for WSNs considering energy constraint	[943]
7.8.	LLACA: an adaptive localized clustering algorithm for wireless ad hoc networks	[46]
7.9.	Density based adaptive soft clustering for optimal energy efficient routing in WSN	[871]
8.	Dynamic clustering:	
8.1.	Dynamic clustering approach with ACO-based mobile sink for data collection in WSNs	[718]
8.2.	Dynamic clustering for reconfiguration of backbone for WSNs	[177]
8.3.	Dynamic clustering method towards improved WSN longevity	[1355]
8.4.	Dynamic cluster head selection method for WSNs	[637]
8.5.	Data similarity aware dynamic node clustering in WSNs	[496]
8.6.	Dynamic clustering for IoT WSNs (Anchor-based routing protocol)	[110]
8.7.	Dynamic clustering approach using multi-verse optimizer for Fog-assisted IoT devices	[116]
9.	Load-balanced clustering:	
9.1.	Load-balanced clustering of WSNs	[533]
9.2.	Optimized and load balanced clustering for WSNs in increase the lifetime	[1051]
9.3.	MCBC: Multi-objective Load Balancing Clustering technique in WSNs	[1057]
9.4.	Optimized and load balanced clustering for WSNs (using MADM approaches)	[1050]
9.5.	Load balanced clustering and dual data uploading in WSNs	[1392]
9.6.	Energy efficient load-balanced clustering algorithm for WSNs	[727]
9.7.	Load-balanced energy efficient clustering protocol for WSNs	[1162]
9.8.	Metaheuristic load-balancing-based clustering technique in WSNs	[299]
9.9.	Modified GA-based load balanced clustering for WSN (MGALBC)	[737]
9.10.	Lightweight load-balanced authentication scheme for a cluster-based WSN	[1412]
9.11.	Load balancing fuzzy-based unequal clustering for WSNs assisted IoT	[34]
10.	Balanced clustering in WSNs:	
10.1.	Balanced clustering for energy efficient routing in WSNs	[959]
10.2.	Energy-balanced clustering routing algorithm for WSNs	[1134,1334]
10.3.	Survey on balanced clustering (in networks)	[771,772]
10.4.	Balanced clustering with full coverage in heterogeneous WSNs	[1362]
10.5.	Energy balanced clustering algorithm in large scope WSN based on cooperative transmission technology	[640]
10.6.	Energy balanced clustering and aggregation for WSNs	[1240]

Table 4.2. Some studies on clustering in WSNs, part 4

No.	Study	Source(s)
11.	Clustering in very large WSNs:	
11.1.	Optimized clustering algorithms for large WSNs (review)	[1094]
11.2.	EEMC: An energy-efficient multilevel clustering algorithm for large-scale WSNs	[641]
11.3.	Collision chain mitigation and hidden device-aware grouping in large-scale 802.1ah networks	[360]
11.4.	Spatiotemporal clustering and compressing schemes for efficient data collection applications in WSNs	[1014]
11.5.	Spectral partitioning and fuzzy C-mean based clustering algorithm for big data WSNs	[1281]
11.6.	Reliable location aware and Cluster-Tap Root based data collection protocol for large scale WSNs	[650]
11.7.	Biologically inspired low energy clustering for large scale WSNs	[1409]
12.	Some other special studies:	
12.1.	Hierarchical clustering-task scheduling policy in cluster-based WSNs	[949]
12.2.	Clustering-based coverage in WSNs	[1361]
12.3.	Cluster-based mobile target detection in WSNs	[1309]
12.4.	Stable femtocells cluster formation in femtocell networks (cooperative game theory)	[1077]
12.5.	Energy efficient clustering scheme using multilevel (multi-hop) routing for WSNs	[932]
12.6.	Differential evolution based clustering algorithm for WSNs	[729]
12.7.	Multifault diagnosis in WSN (clustering, cluster heads selection)	[1201]
12.8.	Link- and hop-constrained clustering for multi-hop WSNs	[316]
12.9.	Energy aware clustering and data gathering technique based on nature inspired optimization in WSNs	[1172]
12.10.	HyperGraph based clustering scheme for power aware WSNs	[486]
12.11.	Robust clustering for extending the lifetime of WSNs	[560]
12.12.	Compressive sensing-based clustering joint annular routing data gathering scheme for WSNs	[1357]
12.13.	Heuristics for designing multi-sink clustered WSN topologies	[1097]
12.14.	Clustering in WSN with latency and energy consumption constraints	[108]
12.15.	Efficient cluster-based self-organization algorithm for WSNs	[759]
12.16.	Novel scheme for wireless sensor-actuator network (WSAN) sink mobility based on clustering and set packing techniques	[940]
12.17.	Bio-inspired clustering scheme for Internet of Drones applications in industrial WSNs	[23]
12.18.	Tree-cluster-based data-gathering algorithm for industrial WSNs with a mobile sink	[1415]
12.19.	Modeling and analyzing cascading dynamics of the clustered WSN	[471]
12.20.	Application-specific clustering in WSNs using combined fuzzy firefly algorithm and random forest	[435]
12.21.	Heuristic angular clustering framework for statistical data aggregation in WSNs	[721]
12.22.	Effective cluster scheduling scheme using local gravitation method for WSNs	[1322]
12.23.	K-means clustering for cell allocation strategies in congested 6TiSCH environments (WSNs)	[706]
13.	Fault-tolerant clustering:	
13.1.	Fault tolerance and energy efficient clustering algorithm in WSNs (FTEC)	[632]
13.2.	Fault-tolerant clustering of WSNs	[532]
13.3.	Efficient fault-prevention clustering protocol for robust underwater sensor networks	[1396]
13.4.	Reliable fault-tolerant model based data aggregation scheme for clustered WSNs	[17]
14.	Clustering in heterogeneous WSNs:	
14.1.	Energy efficient compression sensing-based clustering framework for IoT-based heterogeneous WSN	[869]
14.2.	Hierarchical clustering in heterogeneous WSNs (survey)	[1219]
14.3.	MACCHFL-FT: a fuzzy logic based energy-efficient protocol to cluster heterogeneous nodes in WSNs	[903]
14.4.	GA-based energy-aware multi-hop clustering scheme for HetWSNs	[933]

Table 4.2. Some studies on clustering in WSNs, part 5

No.	Study	Source(s)
15.	Distributed clustering in WSNs:	
15.1.	Distributed clustering in WSNs	[2]
15.2.	Energy-efficient distributed clustering in WSNs	[397]
15.3.	Distributed load balancing clustering algorithm for WSNs	[1286]
15.4.	Distributed load balancing unequal clustering in WSNs (fuzzy approach)	[170]
15.5.	Distributed robust data clustering in WSNs using diffusion moth flame optimization	[714]
15.6.	Sleep-awake energy efficient distributed clustering algorithm for WSNs	[39]
15.7.	Distributed clustering algorithm guided by the base station to extend the lifetime of WSNs (fuzzy clustering procedure)	[1359]
15.8.	Fuzzy-logic based distributed energy-efficient clustering algorithm for WSNs	[1382]
15.9.	Distributed k-means algorithm and fuzzy c-means algorithm for WSN (based on multiagent consensus theory)	[1038]
15.10.	Distributed higher-order k-medoids clustering algorithm for WSN	[907]

4.2. On clustering in networks with moving objects

In recent decades, the role of ad hoc mobile wireless networks (i.e., networks with moving objects) has been increased (e.g., [1096]). The list of moving objects involve the following:

(i) vechicles/cars (i.e., mobile ad hoc networks - VANETs/MANETs);

(ii) flying object as airplanes, drones, UAV, satellites (i.e., UAV networks, flying ad hoc networks - FANETs); etc.

In [25], the following taxonomy of clustering algorithms for MANETs is described:

1. Identifier-based clustering: 1.1 lowest ID cluster algorithm (LIC), 1.2 max-min d-cluster formation algorithm.

2. Connectivity-based clustering: 2.1 highest connectivity clustering algorithm (HCC), 2.2 K-hop connectivity ID clustering algorithm (K-CONID), 2.3 adaptive cluster load balance method, 2.4 adaptive multihop clustering.

3. Mobility-aware clustering: 3.1.mobility-based d-hop clustering algorithm, 3.2. mobility based metric for clustering, 3.3. mobility-based frame work for adaptive clustering.

4. Low cost of maintenance clustering: 4.1. least cluster change algorithm (LCC), 4.2. adaptive clustering for mobile wireless network 4.3. 3-hop between adjacent cluster heads (3-hBAC), 4.4. passive clustering.

5. Power-aware clustering: 5.1. load balancing clustering (LBC), 5.2. power-aware connected dominant set, 5.3. clustering for energy conservation.

6. Combined-weight based clustering: 6.1. weighted clustering algorithm (WCA), 6.2. entropy-based weighted clustering algorithm, 6.3. vote-based clustering algorithm.

In general, the following taxonomy of clustering schemes in MANET is considered (e.g., [25,192,914]): (i) identity based clustering, (ii) topology based clustering, (iii) mobility based clustering, (iv) energy based clustering, (v) weight based clustering, and (vi) AI based clustering. The taxonomy is based on nature of clustering algorithms and criteria for cluster head selection approaches.

In addition, it is reasonable to point out the following basics for the clustering algorithms in MANETs (e.g., [79,192,1221]):

(a) mobility base clustering,

(b) energy-efficient based clustering,

(c) connectivity-based clustering, and

(d) weighted-based clustering.

Some studies on clustering in networks with moving objects (i.e., MANETs, VANETs, FANETs) are pointed out in Table 4.3.

Table 4.3. Some studies on clustering in networks with moving objects, part 1

No.	Study	Source(s)
1.	Some surveys on clustering schemes in MANETs/VANETs:	
1.1.	Surveys on clustering schemes in mobile Ad Hoc networks (MANETs)	[192,914,1345]
1.2.	Survey of clustering techniques for mobile ad hoc networks (MANETs)	[25,79,348]
1.3.	Survey on weighted clustering for mobile ad hoc networks	[1250]
1.4.	Graph theoretic clustering algorithms in MANETs and WSNs (survey)	[428]
1.5.	Comparative study of various clustering algorithms for MANETs	[997]
1.6.	Smart and balanced clustering for MANETs	[341]
1.7.	Clustering schemes in MANETs (performance evaluation, open challenges, and proposed solutions)	[1047]
1.7.	State-of-the-art approach to clustering protocols in VANET (survey)	[671]
1.8.	Review of clustering algorithms in VANETs	[1071]
1.9.	Clustering in vehicular ad hoc network (VANET): algorithms and challenges (machine learning, fuzzy sets, hybrid algorithms, multi-hop strategies)	[926]
1.10.	Clustering review in vehicular ad hoc networks (VANETs) (algorithms, comparisons, challenges)	[619]
1.11.	Survey on intelligent user clustering techniques for NOMA (IoT, 5G networks, RIS, UAVs)	[547]
2.	Studies:	
2.1.	Mobility aware loose clustering for mobile ad hoc networks	[950]
2.2.	Stable zone-based 5G clustered MANET using interest-region-based routing and gateway selection	[71]
2.3.	Self-organization based clustering in MANETs using zone based group mobility	[21]
2.4.	Constructing a MANET based on clusters	[1272]
2.5.	Inter-cluster communication scheme for self-organized transmission power control in MANET clustering	[702]
2.6.	Group mobility based clustering algorithm for mobile ad hoc networks	[256]
2.7.	Efficient weighted distributed clustering algorithm for mobile ad hoc networks	[602]
2.8.	Graph kernel based clustering algorithm in MANETs	[1181]
2.9.	Environment-adaptive distributed node joining approach and a secure cluster-based architecture for MANET	[1167]
2.10.	Node quality based clustering in wireless mobile Ad Hoc networks	[41]
2.11.	Clustering for MANETs based on determination of virtual links' weights (to increase network stability)	[664]
2.12.	Dependability–based clustering in mobile ad hoc networks	[429]
2.13.	SDN-enabled social-aware clustering in 5G-VANET systems	[1032]
2.14.	Cluster-based radio resource management in V2V communications	[5,597]
2.15.	Location-based resource allocation in ultra-dense network with clustering	[694]
2.16.	Junction-based stable clustering algorithm for vehicular ad hoc network	[927]
2.17.	Simple and robust clustering scheme for large-scale and dynamic VANETs	[165]
2.18.	Analysis of new hybrid clustering technique for vehicular ad hoc network	[9]
2.19.	Novelty of hypergraph clustering model for urban scenario in VANET	[618]
2.20.	Extensions in weighted clustering algorithms for mobile Ad Hoc networks	[40]
2.21.	Event message clustering algorithm for selection of majority message in VANETs	[684]
2.22.	Cluster formation and cluster head selection approach for VANETs (using K-means and Floyd-Warshall techniques)	[603]
2.23.	EtHgSC: Eigen Trick-based hypergraph stable clustering algorithm in VANET	[620]

Table 4.3. Some studies on clustering in networks with moving objects, part 2

No.	Study	Source(s)
3.	Optimization approaches:	
3.1.	Ant colony optimization algorithm for multi-objective clustering in mobile ad hoc networks	[1304]
3.2.	Load balanced clustering technique in MANET (evolutionary optimization–genetic algorithms)	[652]
3.3.	Optimizing MANETs network lifetime using a proactive clustering algorithm	[62]
3.4.	Dynamic genetic algorithms for dynamic load balanced clustering in MANETs	[322]
3.5.	Handover minimization in mobile wireless networks (capacitated clustering or node capacitated graph partitioning)	[875,917]
3.6.	Hybrid clustering-based routing protocol for VANET (k-means, maximum stable set problem, hopfield network)	[655]
3.7.	Moth-flame optimization (MFO) based clustering algorithm for VANETs	[1122]
3.8.	Optimization-based advanced cluster head selection for vehicular ad hoc networks	[10]
3.9.	Intelligent Harris Hawks optimization based cluster optimization scheme for VANETs	[600]
3.10.	Multiple criteria clustering of mobile agents in WSN	[1169]
4.	Energy efficient approaches:	
4.1.	Stable energy-efficient location based clustering scheme for ad hoc networks	[910]
4.2.	Energy-efficient clustering in MANETs using multi-objective PSO	[74]
4.3.	Energy and delay efficient dynamic cluster formation using hybrid AGA with FACO in EAACK MANETs	[1099]
4.4.	Clustering algorithm for efficient energy management in mobile ad-hoc networks	[1141]
4.5.	Connectivity, energy and mobility driven clustering algorithm for mobile ad hoc networks	[1221]
5.	Adaptive clustering:	
5.1.	Adaptive clustering for mobile wireless networks	[813]
5.2.	Adaptive clustering using mobile agents in wireless Ad–Hoc networks	[1196]
5.3.	Clustering of mobile Ad Hoc networks: an adaptive broadcast period approach	[485]
5.4.	Adaptive clustering in mobile, multimedia, multihop wireless networks	[531]
5.5.	Adaptive clustering for WSNs with a mobile sink	[1204]
5.6.	Distributed and mobility-adaptive clustering for multimedia support in multi-hop wireless networks	[176]
5.7.	Adaptive clustering algorithm for industrial IoT based mobile opportunistic networks	[1395]
5.8.	Self-adaptable angular based k-medoid clustering scheme for dynamic VANETs.	[206]
6.	Prediction based clustering:	
6.1.	Clustering in mobile ad hoc networks through neighborhood stability-based mobility prediction	[708]
6.2.	Forecast weighted clustering in MANET	[1019]
6.3.	MPBC: a mobility prediction-based clustering algorithm for ad hoc networks	[958]
6.4.	Dynamic clustering algorithm for MANETs by modifying weighted clustering algorithm with mobility prediction	[934]
6.5.	Game theoretic approach for mobility prediction clustering in unmanned aerial vehicle networks	[1315]
7.	Dominating set based clustering algorithms:	
7.1.	(k, r)-dominating set-based, weighted and adaptive clustering algorithms for mobile ad hoc networks	[106]
7.2.	Connected dominating set based clustering algorithm (in MANET)	[1228]
7.3.	Efficient connected dominating set clustering based routing protocol with dynamic channel selection in cognitive radio MANET	[1228]

Table 4.3. Some studies on clustering in networks with moving objects, part 3

No.	Study	Source(s)
8.	Clustering studies for flying ad hoc networks (FANETs):	
8.1.	Bio-inspired clustering schemes for FANETs	[109,680]
8.2.	Self-organization based clustering scheme for FANET using Glowworm Swarm Optimization	[681]
8.3.	Hybrid self-organized clustering scheme for drone based cognitive IoT (Internet of Drones)	[22]
8.4.	Bio-inspired clustering scheme for Internet of Drones applications in industrial WSNs	[23]
8.5.	Clustering strategy of UAV network based on deep Q-learning	[1283]
8.6.	Dynamic clustering mechanism with load-balancing for flying ad hoc networks	[125]
8.7.	Low latency clustering method for large–scale drone swarms	[1417]
8.8.	Improved weighted and location-based clustering scheme for flying Ad Hoc networks (FANETs)	[1331]
8.9.	Game theoretic approach for mobility prediction clustering in unmanned aerial vehicle networks	[1315]
8.10.	Weighting based clustering for FANET	[1284]
8.11.	Energy aware cluster-based routing in FANETs	[1]

5. Applications of basic clustering/grouping approaches/problems

5.1. Network clusters formation

5.1.1. Cluster formation studies

Two basic approaches for cluster formation in networks are usually examined (e.g., [1125]):

Scheme 1: determination of clusters by grouping of network nodes (i.e., clustering) and selection (assignment) of one or more nodes as cluster heads (CHs) for each obtained cluster (Fig. 5.1).

Scheme 2: determination (assignment) of a set of CHs and building the clusters as CHs neighbors (e.g., by proximity) (Fig. 5.2).

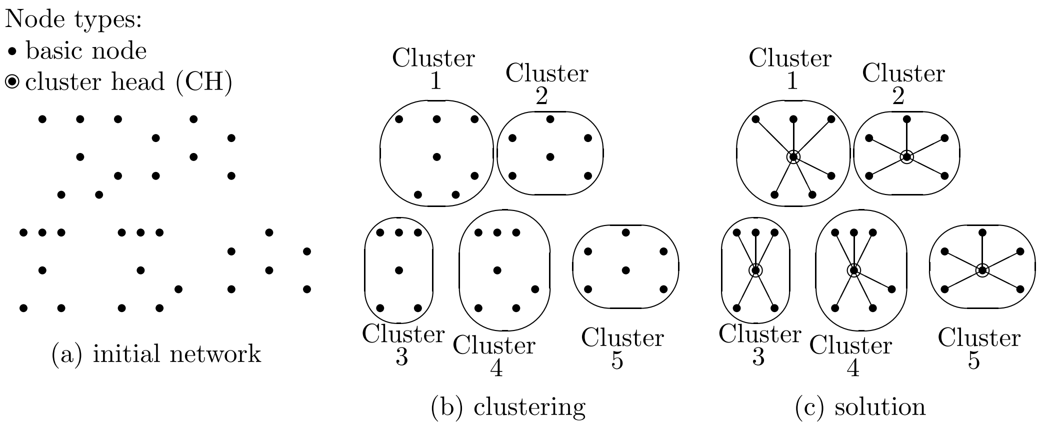


Fig. 5.1. Numerical example for cluster formation (scheme 1)

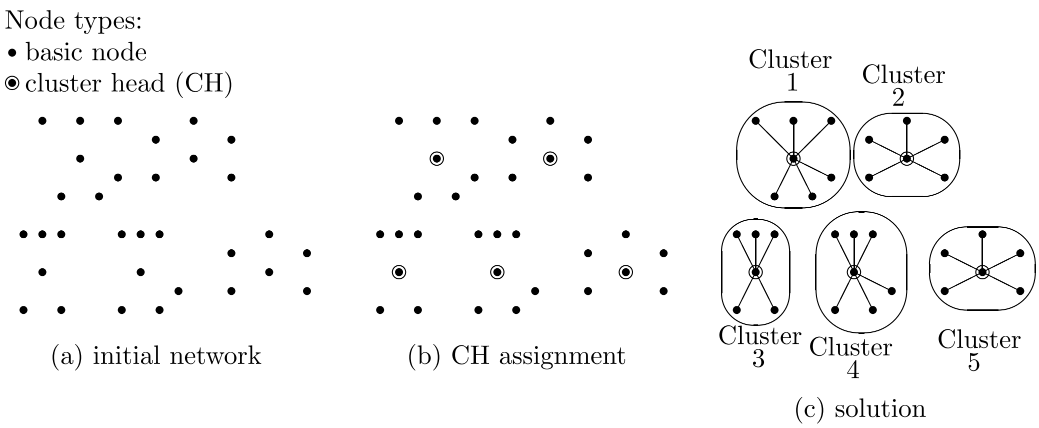


Fig. 5.2. Numerical example for cluster formation (scheme 2)

Some cluster formation studies in communication networks are listed in Table 5.1.

Table 5.1. Some cluster formation studies in communication networks, part 1

No.	Study	Source(s)
1.	Studies on cluster formation:	
1.1.	Energy efficient logic cluster formation protocol in WSNs	[895]
1.2.	Cluster formation in homogeneous WSNs	[938]
1.3.	Machine learning based cluster formation in vehicular communication (V2V)	[202]
1.4.	Mobility-based cluster formation algorithm for wireless mobile ad-hoc networks	[47]
1.5.	Heuristics for designing multi-sink clustered WSN topologies (independent dominating set with connecting requirements)	[1097]
1.6.	Achieving cluster formation of multi agent systems under periodic sampling and communication delays	[487]
1.7.	Identifying large robust network clusters via new compact formulations of maximum k-club problems	[1252]
1.8.	Impact of channel heterogeneity on clustering formation in cognitive ad hoc radio networks	[975]
1.9.	Fuzzy-based cluster head selection and cluster formation in WSNs	[1156]
1.10.	Distributed cluster formation and power-bandwidth allocation for imperfect NOMA in DL-HetNets	[276]
1.11.	Clustering scheme for cluster formation and maintenance in VANETs	[599]
1.12.	Multi-criterion optimization techniques for energy efficient cluster formation in WSNs	[128]
1.13.	Three-stage cluster formation framework for femcell networks	[438]
1.14.	Cluster formation for VANETs (k-means and Floyd-Warshall techniques)	[603]
1.15.	Cluster topology in WSN (with SCPS for QoS)	[1098]
1.16.	Reliable cluster formation in wireless networks with D2D offloading	[1140]
1.17.	Resilient cluster formation for sensor networks	[827]
1.18.	Ranking-based clustering of heterogeneous information networks (star network schema)	[1198]
1.19.	Clustering based on d-hop dominating set for vehicular networks (cluster formation, cluster head selection)	[1149]
2.	Cluster head selection problems:	
2.1.	Low energy adaptive clustering hierarchy (with deterministic cluster-head selection)	[552]
2.2.	HQCA–WSN: High-quality clustering for optimal cluster head selection in WSNs (using fuzzy logic)	[169]
2.3.	Comprehensive review on optimal cluster head selection in WSN-IoT	[1055]
2.4.	Strategic deployment and cluster-head selection for WSNs	[672]
2.5.	Optimized cluster head selection model (energy efficient protocol in WSN)	[70]
2.6.	AI based cluster head selection methodology	[1047]
2.7.	Multi objective Tabu particle swam optimization for effective cluster head selection in WSN	[1255]
2.8.	Taylor kernel fuzzy C-means clustering algorithm for trust and energy-aware cluster head selection in WSNs	[132]
2.9.	Energy based cluster head selection unequal clustering algorithm with dual sink	[66]
2.10.	Cluster head selection in VANETs (k-means and Floyd-Warshall techniques)	[603]
2.11.	Improved Sparrow Search Algorithm for energy efficient cluster head selection in WSNs	[669]
2.12.	Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN	[370]
2.13.	Fuzzy based enhanced cluster head selection (FBECS) for WSN	[889]
2.14.	Multicriteria method for cluster heads selection in WSNs	[1187]
2.15.	Probability-based cluster head selection for prolonging lifetime of WSNs	[1075]
2.16.	Energy efficient cluster head selection for data aggregation in WSNs	[1063]
2.17.	Hybrid cluster head selection model for IoT	[1069]
2.18.	Cluster head selection method for edge computing WSN (improved sparrow search algorithm)	[1041]
2.19.	Optimal selection of the cluster head in WSNs (combination of multiobjective GA and gravitational search algorithm)	[935]
2.20.	Energy-efficient cluster head selection in WSNs (improved Grey Wolf optimization)	[1070]
2.21.	PSO based energy efficient cluster head selection algorithm for WSNs	[1059]

Table 5.1. Some cluster formation studies in communication networks, part 2

No.	Study	Source(s)
3.	Cluster size studies (optimization, etc.):	
3.1.	Cluster size optimization in sensor networks (with decentralized cluster-based protocols)	[89]
3.2.	Max-min d-cluster formation in wireless ad hoc networks	[92]
3.3.	Efficient statistical clustering techniques for optimizing cluster size in WSNs	[418]
3.4.	Cluster size adjustment scheme for cognitive radio networks	[870]
3.5.	Arranging cluster sizes and transmission ranges for WSNs	[741]
3.6.	Cluster-size optimization within a cloud-based ETL framework for Big Data	[1363]
3.7.	Dynamic cluster size optimization in hybrid cellular-vehicular networks	[481]
3.8.	Cluster size optimization in cooperative spectrum sensing	[663]
3.9.	Cluster sizing and for efficient data aggregation and routing in sensor networks	[306]
4.	Cluster numbers selection/optimization studies:	
4.1.	Optimal cluster number selection in Ad Hoc WSNs	[281]
4.2.	Optimal number of clusters in wireless sensor networks (FCM approach)	[1044]
4.3.	Optimizing the number of clusters in multi-hop WSNs	[689]
4.4.	Multi-hop routing-based optimization of the number of cluster-heads in WSNs	[941]

5.1.2. Network modularization

Network modularization problems are targeted to divide an initial network into smaller sub-networks (modules) (e.g., [149,499,952,953,1281]). Some studies in network modularization (problems, approaches, algorithms) are listed in Table 5.2.

Table 5.2. Some studies in network modularization

No.	Study	Source(s)
1.	Modularity and community structure in networks, network modularity optimization	[149,952]
2.	Efficient network modularity optimization	[952,953]
3.	Modularity maximization in networks by variable neighborhood search	[83]
4.	Spectral partitioning and fuzzy C-mean based clustering algorithm for big data wireless sensor networks	[1281]
5.	Using graph partitioning for efficient network modularity optimization	[403]
6.	Partitioning-based divisive clustering technique for maximizing the modularity	[270]
7.	Identifying base clusters and their application to maximizing modularity	[1185]
8.	Network clustering via clique relaxation (community based approach)	[1253]
9.	Modularity and extreme edges of the internet network	[430]
10.	Locally optimal heuristic for modularity maximization of networks	[255]
11.	Column generation algorithms for exact modularity maximization in networks	[82]
12.	Network clustering via maximizing modularity (approximation algorithms and theoretical limits)	[402]
13.	Modularity clustering (graph clustering, graph partitioning, modularity)	[235]
14.	Local modularity measure for network clusterizations	[925]
15.	Multi-level algorithms for modularity clustering (in graphs/networks)	[963]

5.1.3. Femtocells cluster formation

In [1077], the distributed cluster-based resource allocation framework for forming stable clusters of femtocells (based on cooperative game theory) was proposed:

Stage 1. A base station selection algorithm for public user that guarantees them a high data rate.

Stage 2. A coalition game, where femtocells are grouped into stable clusters to reduce the resource allocation complexity,

Stage 3. A fair resource allocation using the Shapley value to compute the payoff of each cluster member based on Particle Swarm Optimization algorithm.

A simplified example of the clustered topology for the macro-femtocell network is depicted in Fig. 5.3 [1077]. Here the following notations are used: macrocell (MC), public user (PU), femtocells (home base stations) (f), subscriber (SU). The following clusters are formed: (i) cluster 1: $X_1 = \{f_1, f_2, f_3\}$; (ii) cluster 2: $X_2 = \{f_6, f_7, f_8\}$; and (iii) cluster 3: $X_3 = \{f_9, f_{10}\}$.

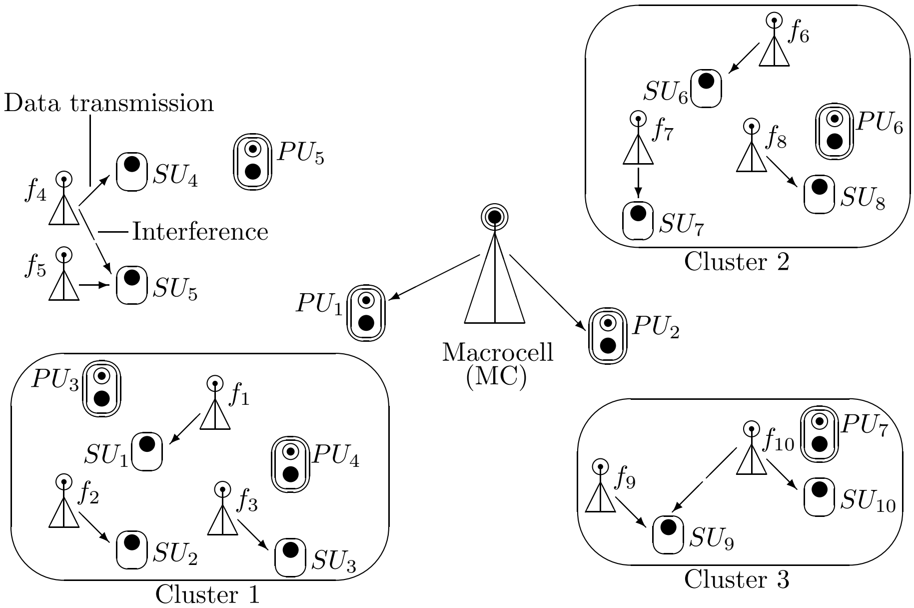


Fig. 5.3. Example of simplified topology of the macro-femtocell network

A three-stage cluster formation framework for femcell networks was proposed in [438]:

Stage 1. BS selection algorithm that balances the traffic load of public users among the clusters.
Stage 2. Cluster formation algorithm that takes into account the cluster size, load and remaining resources.
Stage 3. Particle swam optimization (PSO) algorithm for resource allocation (maximization of the femto tier throughput).

Recently, game theoretical approaches for cluster formations in femtocell networks were proposed:
1. Evolutionary game theoretical model for stable femtocell's cluster formation in HetNets was examined in [1078].
2. Game theoretical framework for joint clustering and resource allocation in macro-femtocell networks is described in [1076].

5.1.4. Dynamic cluster formation in WSNs

The following main approaches for dynamic cluster formation in WSNs are often considered:

Method 1. Robust genetic algorithm for dynamic cluster formation in WSNs [924].

Method 2. Dynamic clustering for reconfiguration (reorganization) of backbone for WSNs [177]:
Stage 1: clustering (clique covering).
Stage 2: selection/assignment of cluster heads.
Stage 3: design of backbone over cluster heads.
Stage 4: obtaining network change (e.g., new node(s)) and re-clustering.
Stage 5: new design (reconfiguration/reorganization) of network backbone (e.g., with new nodes, with new clusters).
In Fig. 5.4, an illustrative example is presented:
(i) initial network (Fig. 5.4a): graph $G = (A, E)$, set of nodes $A = \{1, 2, ..., 22\}$;
(ii) clique clustering (Fig. 5.4b): cluster $X_1 = \{1, 2, 3, 4\}$, cluster $X_2 = \{5, 6, 7\}$, cluster $X_3 = \{8, 9, 10\}$, cluster $X_4 = \{11, 12, 13, 14\}$, cluster $X_5 = \{15, 16, 17, 18\}$, cluster $X_6 = \{19, 20, 21, 22\}$;
(iii) connected backbone (Fig. 5.4c): $B = \{12, 4, 16, 7, 10, 19\}$.

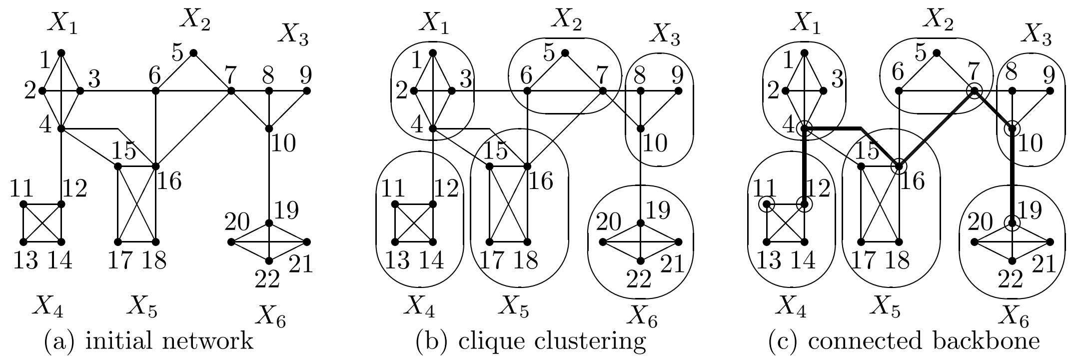


Fig. 5.4. Clustering based backbone design

An illustrative example for reconfiguration (reorganization) of backbone is shown in Fig. 5.5:
(i) reorganized network (Fig. 5.5a, addition of nodes 23 and 24): graph $G' = (A', E')$, set of nodes $A = \{1, 2, ..., 22, 23, 24\}$;
(ii) new clique clustering (Fig. 5.5b): cluster $X_1 = \{1, 2, 3, 4\}$, cluster $X_2 = \{5, 6, 7, 23\}$, cluster $X_3 = \{8, 9, 10, 24\}$, cluster $X_4 = \{11, 12, 13, 14\}$, cluster $X_5 = \{15, 16, 17, 18\}$, cluster $X_6 = \{19, 20, 21, 22\}$;
(iii) new connected backbone (Fig. 5.5c): $B = \{12, 4, 16, 23, 10, 19\}$.

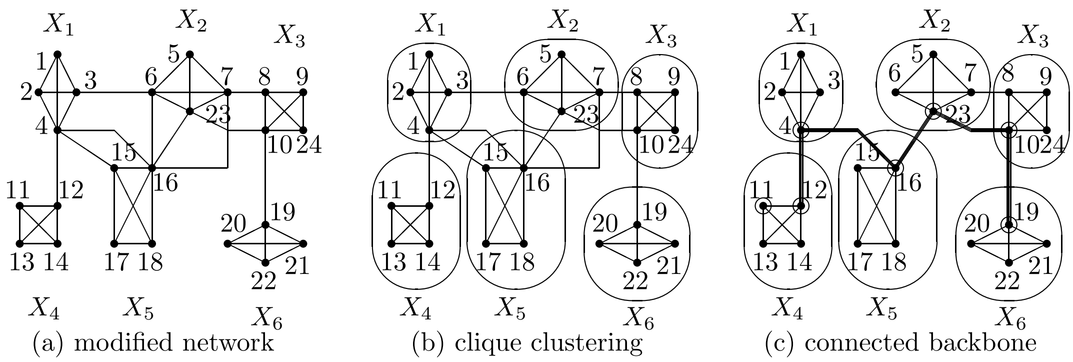


Fig. 5.5. Clustering based backbone design

Method 3. Strategy based on series extension of neighborhood domain(s) (e.g., [66]):
Here the following initial data are used: (a) a central node - static sink (or static base station), (b) some mobile nodes (or mobile base station(s)). The solving scheme is:

Stage 1. Design and analysis of a neighborhood domain:
1.1. CH (heads) selection in near domain.
1.2. Formation of clusters for each CH.
Stage 2. Design and analysis of next neighborhood domain:
2.1. CH (heads) selection in next domain.
2.2. Formation of clusters for each CH.
Stage 3. Design and analysis of next neighborhood domain:
3.1. CH (heads) selection in next domain.
3.2. Formation of clusters for each CH.

Additional stage (e.g., from monitoring in WSNs) can be considered as well: Design of a route through cluster heads to a sensor (or from a sensor).

5.2. Network design (location, hierarchy, k-connectivity)

5.2.1. Some clustering-based topology design problems

Some studies on clustering-based topology design problems are pointed out in Table 1004.

Table 5.3. Some studies on clustering-based topology design problems

No.	Study	Source(s)
1.	Optimal clustering structures for hierarchical topological design of large computer networks	[700]
2.	Comparison of different logical topologies for WSNs (cluster topology of WSNs)	[868]
3.	Heuristics for designing multi-sink clustered WSN topologies (Independent Dominating Set with connecting requirements)	[1097]
4.	Clustering algorithm for the topological design of hierarchical, multidrop data networks	[1257]
5.	Mulicriteria Steiner tree problem design: (i) clustering of the initial network (ii) design of structure for each cluster (iii) integration of local solutions into the total structure	[786,787]
6.	Low energy adaptive clustering hierarchy (with deterministic cluster-head selection)	[552]
7.	Clustering algorithm for the topological design of hierarchical, multidrop data networks	[1257]

5.2.2. k-center problems or allocation of network hubs

Given a graph $G = (A, E)$ (A is the vertex set, E is the edge set) with edge lengths (weights). The k-center problem is targeted to selection of a subset of vertices/nodes (i.e, k-centers or p-centers as hubs) to provide a restricted proximity from any vertex/node to the nearest center vertex/node [453]. The basic problem is:

Find the set of k center vertices in G (i.e., a subset of A such that the "distance" from any vertex of G to its nearest center is minimized.

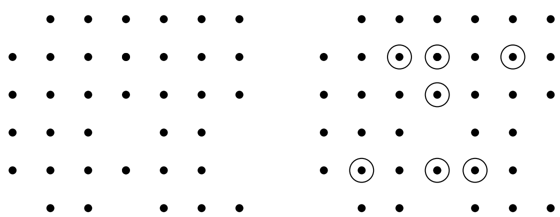
The classic p-center problem consists of selecting a set of p vertices (centers) in a undirected graph as facilities in order to minimize the maximum distance between each client-end user vertex and its closest facility (e.g., [369,482,665]). This problem is equivalent to covering all vertices by more than p circles with the smallest possible radius, which can be tackled by solving a series of the decision version of set covering subproblems with the same cardinality constraint ($\leq p$) and gradually decreasing the covering radius. The p-center problem belongs to the class of NP-hard problems [665].

The problem has a wide range of applications, for example: (1) optimal locations of switching centers in a communication networks (e.g., [545]); (2) determination of the locations of emergency centers (e.g., [1224]).

Some simplified illustrations for the p-center problem are depicted in Fig. 5.6 and Fig. 5.7:

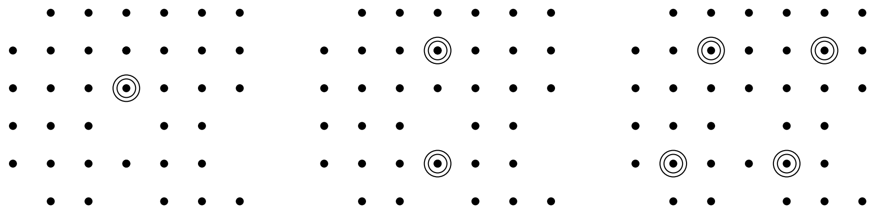
(i) initial data: (a) set of vertices (Fig. 5.6a), (b) center candidates (Fig. 5.6b);

(ii) illustrative example of solutions: (a) 1-center solution (Fig. 5.7a), (b) 2-center solution (Fig. 5.7b), and (c) 4-center solution (Fig. 5.7c).



(a) initial vertices (b) center candidates

Fig. 5.6. Initial data for p-center problem example



(a) 1-center solution (b) 2-center solution (c) 4-center solution

Fig. 5.7. Illustration for p-center solutions

Fig. 5.8 depicts an example of three-layer network (single allocation of terminal to hub):

I. Layer of central hub (single).
II. Layer of hub as fully interconnected network (clique, nodes $\{1,2,3,4\}$).
III. Layer of terminal nodes: (3.1) star network for hub 1: $\{t_{11},t_{12}\}$, (3.2) tree network for hub 2: $\{t_{21},t_{22},t_{23},t_{211},t_{212},t_{231},t_{232}\}$, (3.3) clique/cycle network for hub 3: $\{t_{31},t_{32},t_{33}\}$, and (3.4) star network for hub 4: $\{t_{41},t_{42}\}$.

An example of the corresponding hierarchical (three-layer) network with three central hubs is depicted in Fig. 5.9 (with central hub subnet). Here, central hub subnet are fully interconnected (i.e., clique structure).

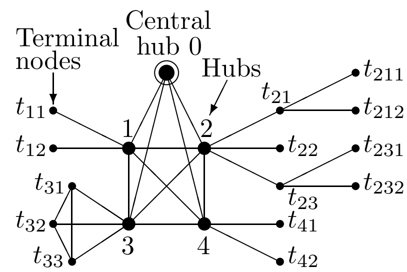


Fig. 5.8. 3-layer network (hub subnet)

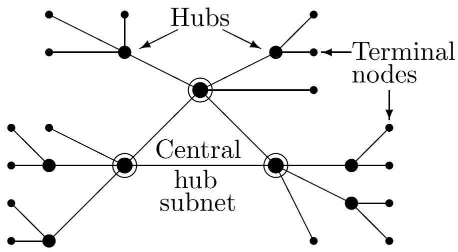


Fig. 5.9. 3-layer network (central hub subnet)

In general, the scheme of hub location in communication networks is targeted to the design of multi-layer (multi-tier) network topology. Here several corresponding combinatorial solving facility assignment/location schemes are used (e.g., [262,263,446]). At the same time the above-mentioned solving schemes involve the clustering problems as a basic auxiliary problem. For example the following solving scheme can be used:
(1) clustering of the set of initial network nodes,
(2) selection/assignment of cluster heads (as prospective hub candidates),
(3) selection/assignement of the set of the resultant hub subset, and
(4) connection of the selected hubs and/or designing a hub net.

5.2.3. Design of multi-layer (mobile) network

Some schemes of designing multi-tier networks are as follows:
Scheme 1. Design of multi-layer network [765,767].

Scheme 2. Design of a 3-layer network architecture [1392]:
Layer 1 (top) (SenCar Layer - mobile collector). pooling points
Layer 2 (mediate, Cluster Head Layer). cluster head groups
Layer 3 (bottom) (Sensor Layer). sensor clusters

An illustrative multi-layer network structure based on balanced clustering is shown in Fig. 5.10.

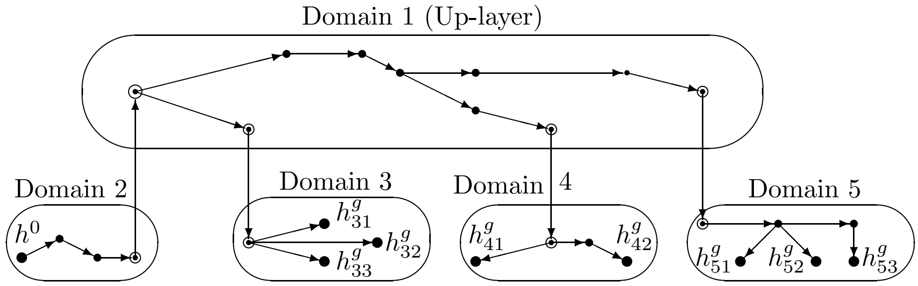


Fig. 5.10. Balanced clustering based multi-layer network structure

Fig. 5.11 illustrates five stage scheme for designing a clustering-based three-layer network (e.g., WSNs, mobile networks) [216,701,767]:

Stage 1. Clustering (e.g., clique/quasi-clique based clustering) of the initial set of nodes.

Stage 2. Selection/assignment of clusterhead for each obtained cluster.

Stage 3. Clustering (e.g., clique/quasi-clique based clustering) of the set of cluster heads.

Stage 4. Selection/assignment of top-level clusterhead for each obtained clusterhead cluster.

Stage 5. Connection (e.g., via cluster gateways) of the obtained top level clusterheads and the main central network head node (root).

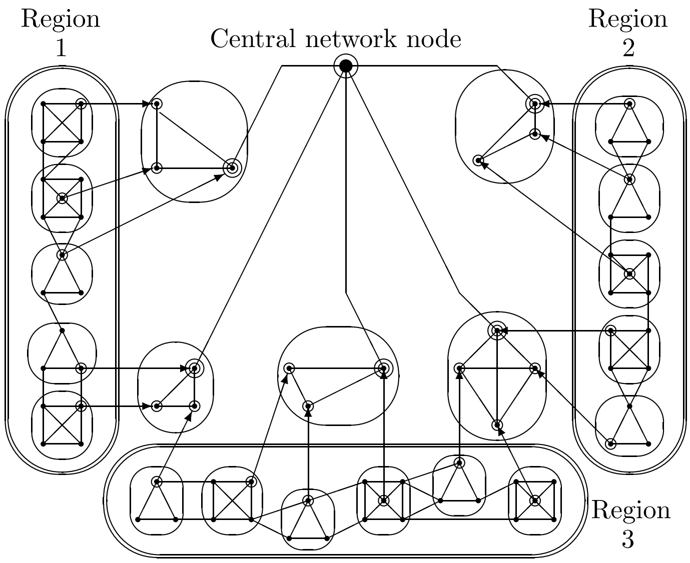


Fig. 5.11. Clustering based three-layer network structure

In addition the following hybrid clustering schemes are used for the design of multi-layer networks:

1. Geocasting, multi-geocasing [701].

2. Hybrid clustering schems for WSNs [216]:

(2.1) partitioning the network in cliques using en existing energy-efficient hierarchical clustering,

(2.2) set of clusterheads of cliques are partitioned using of energy-efficient hierarchical clustering (clusterhead is located in the central area of the cluster).

3. The network is partitioned geographically [287]:

Cellular-based-management geographically partitions the network into several disjoints and equally sized cellular regions.

A traditional multi-layer architecture of WSN (Fig. 5.12) consist of the following layers [218,1270]: (1) sensors, (2) clusters, (3) cluster heads, (4) sink, (5) database server, and (6) decision/control center.

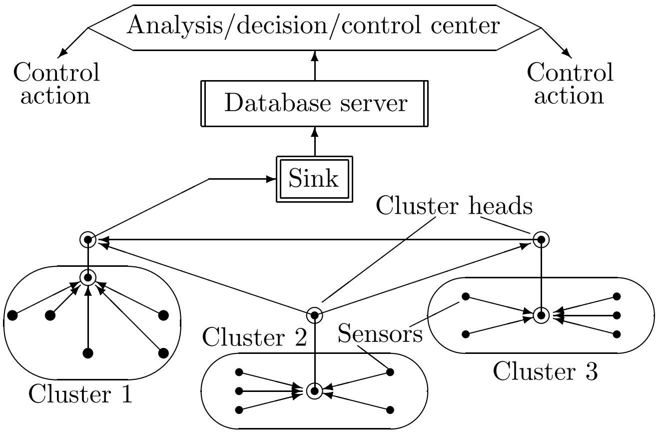


Fig. 5.12. Multi-layer architecture of WSN

5.2.4. Balancing-based problems

Load-balanced clustering problems in the network design are targeted to increasing the system stability and improving the communication between the various nodes in the networks (e.g., [849]). The general case of the load-balanced clustering problem is NP-hard [849].

Some load-balanced clustering studies are listed in Table 5.4.

Table 5.4. Some load-balanced clustering studies

No.	Study	Source(s)
1.	Load-balanced clustering in WSN:	
1.1.	Load-balanced clustering in WSN	[849,1025,1155,1392]
1.2.	Load-balancing cluster head (LBCH) protocol for WSNs	[64]
1.3.	Load-balancing in heterogeneous WSNs	[616]
1.4.	Optimized and load balanced clustering for WSNs to increase the lifetime of WSNs (using MADM approaches)	[1050]
1.5.	Energy efficient load-based clustering method for mobile WSNs	[65]
2.	Dynamic load balancing in networks:	
2.1.	Dynamic load balancing through association control of mobile users in WiFi networks	[504]
2.2.	Dynamic genetic algorithms for dynamic load balanced clustering problem in mobile ad hoc networks (dynamic genetic algorithms)	[322]
2.3.	GACO - hybrid ant colony optimization metaheuristic for dynamic load-balanced clustering in Ad Hoc networks	[579]
3.	Some other balance studies in networks:	
3.1.	Load balancing for QoS optimization in wireless LANs	[237]
3.2.	Load balancing clustering method for the RPL protocol (IoT)	[447]
3.3.	Distributed delay-balancing slot allocation algorithm for 802.11s mesh coordinated channel access under dynamic traffic conditions	[761]
3.4.	Load-balanced cluster head selection enhancing network lifetime in WSN using hybrid approach for IoT applications (multicriteria method)	[1187]
4.	Traffic balancing in networks:	
4.1.	Traffic balancing in heterogeneous networks (optimal power allocation, optimal time allocation)	[797]
4.2.	Traffic aware balancing for mobile ad-hoc networks	[996]

5.3. Clustering-based problems

5.3.1. Dynamic clustering and resource allocation

Some dynamic clustering studies for resource allocation are listed in Table 5.5.

Table 5.5. Some dynamic clustering and resource allocation studies

No.	Study	Source(s)
1.	Dynamic clustering and resource allocation algorithm for downlink CoMP systems with multiple antenna UEs	[168]
2.	Dynamic clustering approach in wireless networks with multi-cell cooperative processing	[991]
3.	Dynamic clustering for multi-user distributed antenna system	[828]
4.	Dynamic joint clustering scheduling for downlink CoMP systems with limited CSI	[167]
5.	Dynamic clustering of base stations for future wireless networks	[992]
6.	Dynamic resource allocation in cloud computing based on workflow and resource clustering	[1135]
7.	Cluster frameworks for efficient scheduling and resource allocation in data center networks (survey)	[1280]
8.	Resource assignment based on dynamic fuzzy clustering in elastic optical networks	[1329]
9.	Deep reinforcement learning for dynamic clustering and resource allocation in smart-duplex networks	[1287]

5.3.2. Clustering-based routing

Some general clustering-based routing studies are pointed out in Table 5.6.

Table 5.6. Some general clustering-based routing studies

No.	Approach	Source(s)
1.	Some surveys on clustering based routing protocols in WSNs:	
1.1.	Survey on cluster based routing protocols in WSNs	[148,1170]
1.2.	Survey on clustering routing protocols in WSNs	[832]
2.	Soe general studies on clustering-based protocols:	
2.1.	Scaling hierarchical clustering and energy aware routing for sensor networks	[1120]
2.2.	Energy-efficient clustering routing for WSNs (energy consumption optimization)	[598]
2.3.	Energy-aware clustering-based routing in wireless sensor networks using Cuckoo optimization algorithm	[675]
2.4.	Energy-aware multilayer clustering-based butterfly optimization routing for underwater WSNs	[327]
2.5.	Multi-hop routing with static and distributed clustering in WSNs	[2]
2.6.	Fault-tolerant clustering-based multipath routing for WSNs	[918]
2.7.	Probability-based cluster head selection and fuzzy multipath routing for prolonging lifetime of WSNs	[1075]
2.8.	Energy-efficient chain-cluster based intelligent routing technique for WSNs	[1053]
2.9.	Multi-objective Cluster Head Based Energy-aware Optimized Routing algorithm on WSNs	[1102]

Table 5.7 contains an extended list of studies on clustering-based network protocols.

Deployment of Internet routing protocol is based on clustering as well. Here a three-phase design scheme for deployment of Internet routing protocol (partitioning-hub-location-routing problem) is used [272]:

Phase 1. Partitioning (clustering) a given network into sub-networks (areas).
Phase 2. Location of hubs over the network (at least one hub in each sub-network).
Phase 3. Routing the traffic within the network at minimum cost.

The problem is problem above is formulated as size-constrained clique partitioning model (graph partitioning) and mixed integer programming model and branch-and-cut algorithm is applied.

Table 5.8 contains a list of studies on clustering-based multi-path routing in WSNs.

Table 5.7. Basic clustering routing protocols, part 1

No.	Approach	Source(s)
1.	Basic well-known clustering based routing protocols:	
1.1.	LEACH (and its modifications)	[570,571,738] [916,1178,1236]
1.2.	HEED (multi-hop path created on the CHs)	[1343]
1.3.	EHEED extends the HEED by multi-hop intra-cluster transmissions	[1115]
1.4.	PEACH: power-efficient and adaptive clustering hierarchy protocol for WSNs	[1338]
1.5.	DHCR: energy-aware clustering protocol	[1084]
1.6.	EDIT: low cost clustering protocol (minimum number of messages exchanged among sensor nodes)	[1213]
2.	Optimization and evolutionary approaches:	
2.1.	Clustering protocol for energy balance of WSN based on genetic clustering algorithm	[565]
2.2.	Evoluonary based routing protocol for clustered heterogeneous WSNs	[130]
2.3.	Efficient connected dominating set clustering based routing protocol with dynamic channel selection in cognitive radio MANET	[1228]
2.4.	Clustering routing based on mixed integer programming for heterogeneous WSNs	[798]
2.5.	Clustering routing protocol for energy balance of WSN based on simulated annealing and genetic algorithm	[1378]
2.6.	Cluster based WSN routing using artificial bee colony algorithm	[661]
2.7.	Hierarchical adaptive routing algorithm of WSN based on SDN (cluster based routing, multiple choice knapsack problem)	[1394]
2.8.	Energy-efficient cluster-based routing protocol using unequal clustering and improved ant colony optimization for WSNs	[923]
2.9.	Adaptive clustering based dynamic routing of WSNs via generalized ant colony optimization	[1337]
2.10.	Cluster routing algorithm for ring based WSN using particle swarm and Lion swarm optimization	[592]
3.	AI-based approaches:	
3.1.	Swarm intelligence based fuzzy routing protocol for clustered WSNs	[1360]
3.2.	Energy aware cluster and neuro-fuzzy based routing algorithm for WSNs in IoT	[1214]
3.3.	Power efficient cluster-based routing for WSNs (honeybees swarm intelligence approach)	[115]
3.4.	Energy-efficient QoS-aware intelligent hybrid clustered routing protocol for WSNs	[1171]
3.5.	CMML: combined metaheuristic-machine learning for adaptable routing in clustered WSNs	[434]
4.	Multi-hop cluster routing:	
4.1.	Energy-efficient multi-hop routing protocol based on grid clustering for WSNs	[596]
4.2.	Energy efficient clustering scheme using multilevel (multi-hop) routing for WSNs	[932]
4.3.	Fuzzy-based multi-hop unequal cluster routing (SDN, WSN)	[851]
4.4.	Energy-efficient clustering-based routing scheme in multi-hop underwater sensor networks (USNs)	[690]
4.5.	Evidence-efficient multihop clustering routing scheme for large-scale WSNs	[796]
4.6.	EA-CRP: novel energy-aware clustering and routing protocol in WSNs (multi-hop routing, multilayer topology, network lifetime)	[362]
4.7.	Multi-hop routing with static and distributed clustering in WSNs	[2]
4.8.	Weighted energy consumption minimization-based multi-hop uneven clustering routing protocol for cognitive radio sensor networks	[1288]

Table 5.7. Basic clustering routing protocols, part 2

No.	Approach	Source(s)
5.	Fuzzy set based approaches:	
5.1.	Triangular fuzzy-based spectral clustering for energy-efficient routing in WSNs	[961]
5.2.	Fuzzy-based multi-hop unequal cluster routing (SDN, WSN)	[851]
5.3.	Energy aware cluster and neuro-fuzzy based routing algorithm for WSNs in IoT	[1214]
5.4.	Hierarchical clustering approach for mobile sensor WSN using fuzzy inference systems (low-energy adaptive clustering hierarchy protocol)	[757]
6.	Adaptive cluster based routing protocols:	
6.1.	Novel adaptive cluster based routing protocol for energy-harvesting WSNs	[551]
6.2.	Hierarchical adaptive routing algorithm of WSN based on SDN (cluster based routing, multiple choice knapsack problem)	[1394]
6.3.	Adaptive clustering based dynamic routing of WSNs via generalized ant colony optimization	[1337]
6.4.	Hierarchical clustering approach for mobile sensor WSN (low-energy adaptive clustering hierarchy protocol)	[757]
7.	Special clustering based routing protocols:	
7.1.	Hierarchical cluster-based routing in WSNs	[601]
7.2.	Energy-efficient clustering-based mobile routing for WSNs (clustering, CH selection)	[662,1386]
7.3.	QoS-aware and heterogeneously clustered routing protocol for WSNs	[93]
7.4.	Unequal cluster based routing protocol in WSNs	[312,1416]
7.5.	Novel cluster-based energy efficient routing in WSNs	[867]
7.6.	Automatic clustering for routing in multilevel networks	[1292]
7.7.	Balanced clustering for energy efficient routing in WSNs	[959]
7.8.	Cluster-based energy-efficient routing in WSNs	[861]
7.9.	Energy-efficient routing based on unequal clustering and connected graph in WSNs	[1312]
7.10.	Energy efficient clustering protocol to enhance performance of heterogeneous WSN (EECPEP-HWSN)	[1031]
7.11.	Distance-based and low energy aware clustering protocol for WSNs	[809]
7.12.	Energy-efficient heterogeneous ring clustering routing protocol for WSNs	[1381]
7.13.	Cluster-based trusted routing method using fire hawk optimizer (FHO) in WSNs	[587]
7.14.	HEEP (hybrid energy-efficient protocol) based on chain clustering	[228]
8.	Clustering based routing for WSNs in IoT:	
8.1.	Enhanced three layer hybrid clustering mechanism for energy efficient routing in IoT (three layer clustering topology in WSNs)	[1238]
8.2.	Clustering routing algorithm and simulation of IoT perception layer	[1320]
8.3.	Clustering based routing algorithm in IoT aware Wireless Mesh Networks	[799]
8.4.	Optimal cluster-based routing algorithm for the lifetime maximization of clustered IoT supported WSN	[1335]
8.5.	Dingo optimization based cluster based routing in IoT	[112]
8.6.	Anchor-based routing protocol with Dynamic clustering for IoT WSNs	[110]
8.7.	Cluster-based routing protocol with static hub (CRPSH) for WSN-assisted IoT networks	[760]

Table 5.8. Clustering-based multipath routing in WSNs

No.	Problem type/approach	Source(s)
1.	Energy-efficient multipath routing protocol for WSNs	[900]
2.	Multi-path routing in space information networks	[488]
3.	Multipath routing in wireless multimedia sensor networks	[585]
4.	Fuzzy multipath routing for prolonging lifetime of WSNs	[1075]
5.	Environment-fusion multipath routing protocol for WSNs	[472]
6.	Novel fault-tolerant clustering-based multipath algorithm (FTCM) for WSNs	[918]
7.	Cluster aided multi-path routing protocol for WSNs	[1093]
8.	Energy-efficient and scalable multipath routing protocol for WSNs	[257]
9.	Evolutionary multipath energy-efficient routing protocol (EMEER) for network lifetime enhancement in WSNs	[441]
10.	Multipath routing through the firefly algorithm and fuzzy logic in WSNs	[1123]
11.	Distributed multi-path routing algorithm to balance energy consumption in WSNs	[748]
12.	Multipath-based routing protocol in hierarchical WSN	[909]
13.	Energy-efficient optimal multi-path routing protocol to in WSN for IoT applications	[626]
14.	Efficient multipath routing protocol against path failures in WSNs	[1339]

5.3.3. Clustering for control in communication networks

The placement of various nodes (e.g., base stations, controllers, concentrator, gateway nodes, router nodes, relay sensors, access points) in a communication network is often based on the preliminary division of the network into clusters (e.g., [193,726,850,1186,1215,1275]). Some studies of clustering based controller placement problems in a communication network are listed in Table 5.9.

Table 5.9. Some studies of clustering based controller placement

No.	Study	Brief description	Source(s)
1.	Clustering-based network partitioning algorithm (CNPA)	Partitioning the network to maximize end-to-end latency between controllers and their associated switches	[1275–1277]
2.	Density cluster based approach	Controller placement problem in large-scale SDNs	[808]
3.	Cluster leader election problem	Distributed controller placement in SDN	[611]
4.	Multicriteria clustering approach	Framework for reliable controller placement in SDNs	[627]
5.	Clustering based MCDM scheme (AHP) (preliminary network clustering)	Controller placement	[76]

An additional list of clustering based controller placement problems in communication networks (mainly in SDNs) is presented in Table 5.10.

Table 5.10. Some studies on clustering based controller placement

No.	Study	Source(s)
1.	Cooperative game theory based network partitioning for controller placement in SDN	[686]
2.	K-means-based network partition algorithm for controller placement in SDN	[1275]
3.	Spectral clustering based approach for controller placement problem in software defined networking	[850]
4.	Hierarchical k-means algorithm for controller placement problem	[726]
5.	Fuzzy C-means for controller placement in software defined networking	[1215]

Clustering schemes are used for hierarchical control in multi-hop networks:

1. Clustering scheme for hierarchical control in multi-hop wireless networks [163]
2. Cluster-based distributed medium access control protocol for multichannel and multihop mobile cognitive radio ad hoc networks [1310].

5.3.4. Clustering for network lifetime maximization

Some studies on clustering for enhancing the lifetime of networks are listed in Table 5.11.

Table 5.11. Some studies on clustering for enhancing the lifetime of networks

No.	Study	Source(s)
1.	Clustering for network lifetime maximization (e.g., for WSNs, IoT) (energy efficient equal/unequal size clustering)	[546]
2.	Load-balanced cluster head selection enhancing network lifetime in WSN using hybrid approach for IoT applications (multicriteria method)	[1187]
3.	Fuzzy clustering algorithm for enhancing reliability and network lifetime of WSN	[750]
4.	Clustering enhanced approach for network lifetime in WSN	[653]
5.	Fuzzy logic-based clustering algorithm for WSN to extend the network lifetime	[946]
6.	Dynamic clustering method towards improved WSN longevity	[1355]
7.	Distributed on-demand clustering algorithm for lifetime optimization in WSNs	[495]
8.	Improving the lifespan of WSNs with fuzzy based clustering and machine learning	[1043]
9.	Clustering algorithms for maximizing the lifetime of WSNs with energy-harvesting sensors	[1376]
10.	Energy efficient clustering algorithm for maximizing lifetime of WSNs	[899]
11.	Energy efficient clustering scheme for prolonging the lifetime of WSN with isolated nodes	[762]
12.	Balanced cluster size solution to extend lifetime of WSNs	[983]
13.	Improved energy-efficient clustering protocol to prolong the lifetime of the WSN-based IoT	[559]
14.	Robust clustering for extending the lifetime of WSNs in an optimized manner	[560]
15.	Improvement of WSN lifetime via intelligent clustering under uncertainty	[1091]
16.	Constructing optimal clustering architecture to maximize sensor network lifetime	[794]
17.	Prolonging the lifetime of WSNs via unequal clustering	[1182]

5.3.5. Clustering in spectrum sensing

Spectrum sensing is targeted to analyze the primary users in cognitive radio networks for dynamic reorganization of spectrum access operations (e.g., [60,119,420,562,1193]). Cluster-based cognitive radio networks have been considered in [310,311,752,830,846]. Clustering in spectrum sensing for a cognitive radio network is a basis of the used hierarchical network architecture [392,420]. Fig. 5.13 illustrates a centralized cooperative spectrum sensing that is based on a clustered network [392].

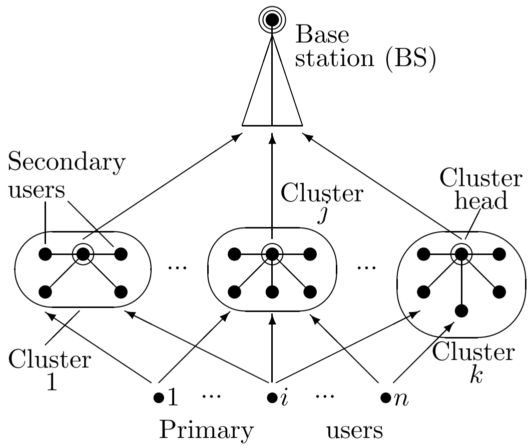


Fig. 5.13. Centralized cooperative spectrum sensing

Some studies on clustering in spectrum sensing are pointed out in Table 5.12.

Table 5.12. Some studies on clustering in spectrum sensing

No.	Study	Source(s)
1.	Spectrum sensing for cognitive radio	[562]
2.	Spectrum sensing for cognitive radio (fundamentals and applications)	[268]
3.	Review on spectrum sensing for cognitive radio (challenges and solutions)	[1398]
4.	Soft computing techniques for spectrum sensing in cognitive radio network (survey)	[420]
5.	Spectrum sensing techniques in cognitive radio networks (survey)	[1193]
6.	Cluster based cooperative sensing (survey)	[392]
7.	Spectrum sensing for cognitive radio (recent advances and future challenge)	[944]
8.	Comprehensive survey on spectrum sensing in cognitive radio networks (recent advances, new challenges, and future research directions)	[119]
9.	Survey of spectrum sensing algorithms for cognitive radio applications (multi-dimensional spectrum sensing, cooperative sensing)	[1358]
10.	Cooperative spectrum sensing in cognitive radio networks (survey)	[60]
11.	Spectrum sensing in cognitive radio networks (threshold optimization and analysis)	[704]
12.	Spectrum sensing performance of cluster-based cooperative cognitive radio networks via sequential multiple reporting channels	[586]
13.	Optimization of spectrum sensing for opportunistic spectrum access in cognitive radio networks	[492]
14.	Cluster-CMSS: a cluster-based coordinated spectrum sensing on geographically dispersed mobile cognitive radio networks	[1127]
15.	Clustering methods for distributed spectrum sensing in cognitive radio systems	[863]
16.	Cluster-based adaptive multi spectrum sensing and access in cognitive radio networks	[1375]
17.	Energy efficient clustering approach for cooperative spectrum sensing in cognitive radio networks	[715]
18.	Energy-efficient spectrum aware clustering for cognitive radio sensor networks	[1374]
19.	Sensing-throughput tradeoff in cluster-based cooperative cognitive radio networks	[480]
20.	Spectrum sensing, clustering algorithms, and energy-harvesting technology for cognitive-radio-based IoT technology	[459]

Table 5.13. Some clustering-based target detection/tracking studies

No.	Study	Source(s)
1.	Basic target detection/tracking studies:	
1.1.	Real-time object tracking (monitoring) (e.g., tracking and management of vehicles in industrial region; approach based on clustering - multi-level network - routing)	[1231]
1.2.	Dynamic clustering for target tracking in WSNs	[308,1325]
1.3.	Auction-based adaptive sensor activation algorithm for target tracking in WSNs (clusters a formed ahead of the target movements)	[1400]
1.4.	Cluster-based mobile target detection in WSNs	[1309]
2.	Multi-target detection/tracking:	
2.1.	Clustering for multi-target tracking	[607]
2.2.	Hierarchical clustering for multi-target, multi-camera tracking	[1383]
2.3.	Multi-class classification and clustering based multi-object tracking	[1184]
2.4.	Dynamic cluster assignment for multi-target tracking in heterogeneous WSNs	[936]
2.5.	Multi-sensor multi-target tacking using domain knowledge and clustering	[566]

5.3.6. Clustering-based target detection/tracking

Energy-efficient real-time object tracking (monitoring) in multi-level sensor networks by mining and predicting movement patterns (e.g., tracking and management of vehicles in industrial region) [1231]:

Stage 1. Hierarchical clustering of network nodes to form a hierarchical (multi-level) sensor network.

Stage 2. Data mining to obtain moving patterns (to predict the next position of a moving object).

Stage 3. Tracking (monitoring) of moving objects (on the basis of multilevel architecture of network nodes).

Another approach is as follows: dynamic clustering for target tracking in WSNs [308,1325]. Cluster-based mobile target detection in WSNs is described [1309]. Table 5.13 contains a list of some research efforts in clustering-based target selection/detection/tracking studies.

5.3.7. Capacitated clustering for minimum handover in mobile networks

Capacitated clustering problem (or node capacitated graph partitioning problem) is used for handover minimization in mobile wireless networks (Fig. 5.14) (e.g., [782,875,917]).

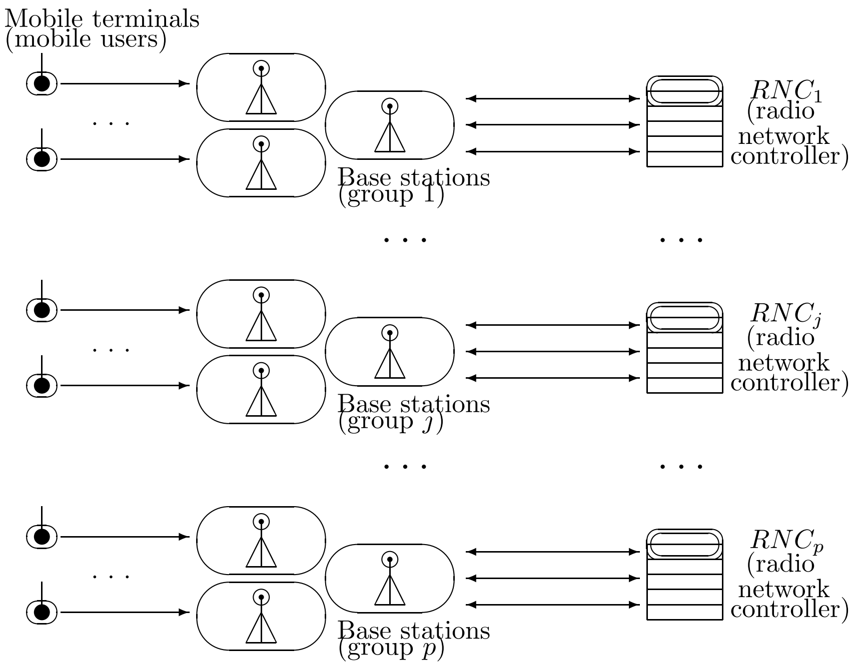


Fig. 5.14. Illustration of handover minimization in mobile wireless networks [782]

A mobility network (Fig. 5.14) contains radio network controllers (RNC) for controlling the base station operations (including traffic and handover). The set of base stations assigned to a RNC can be viewed as a cluster, and the minimization of handovers between different clusters is equivalent to the maximization of handovers within the same cluster. Therefore, this problem is equivalent to the CCP:

Find an assignment of each base station (in set of base stations T) to some RNC (radio network controller) in set of the controllers R.

Another description of the problem is:

Find a partition of a set V of n nodes (base stations) into p clusters (groups of base stations - each group is assigned to the same controller)) such that:
(a) the sum of benefits c_e, of edges $e \in E$ within each cluster is maximized, and
(b) the sum of the node weights, $w_i \geq 0$ of nodes $i \in V$ within the same cluster is within some integer capacity limits: L and U ($L < U$).

5.3.8. Traffic classification

Data on network traffic is an important initial information for analysis, modeling, monitoring, and management of network. Traffic classification is often considered as a basis for network management. Table 5.14 contains a list of some studies in network traffic classification.

Table 5.14. Some studies in network traffic classification

No.	Research	Source(s)
1.	Surveys:	
1.1.	Deployment of machine learning solutions in network traffic classification (systematic survey)	[982]
1.2.	Reviewing traffic classification	[1243]
1.3.	Comparative analysis of techniques for network traffic classification (machine learning algorithms)	[1119]
1.4.	Issues and future directions in traffic classification	[359]
1.5.	Independent comparison of popular DPI tools for traffic classification	[250]
2.	Support vector machine for traffic classification:	
2.1.	Multi class SVM algorithm with active learning for network traffic classification	[407]
2.2.	Support Vector Machines for TCP traffic classification	[437]
2.3.	Internet traffic classification based in incremental support vector machine	[1199]
3.	Machine learning methods for traffic classification:	
3.1.	Approach for internet traffic classification (machine learning)	[431]
3.2.	Machine learning solutions in network traffic classification	[982]
3.3.	Network traffic classification techniques using machine learning algorithms	[1119]
3.4.	Robust network traffic classification (scheme for combination of supervised and semi-supervised learning)	[1377]
4.	Evolutionary classifiers for traffic classification:	
4.1.	Explainable internet traffic classification (multi-objective evolutionary learning scheme)	[260]
4.2.	Internet traffic classification based on multi-objective evolutionary fuzzy classifiers	[416]
4.3.	Genetic algorithm for internet traffic classification	[431]
5.	Special methods for traffic classification:	
5.1.	Imbalanced data classification based on data gravitation (for imbalanced traffic identification)	[1010,1011]
5.2.	Efficient and robust feature extraction and selection for traffic classification	[1150]
5.3.	Self adaptive network traffic classification	[1222]
5.4.	Multi-class imbalanced network traffic datasets based on local and global metric fusion	[837]
5.5.	Optimization of traffic classification	[1373]
5.6.	Internet traffic classification using a supervised Spiking Neural Network	[1061]
5.7.	Bayesian neural networks for internet traffic classification	[133]
5.8.	Robust application methods for P2P and VoIP traffic classification in backbone networks (sampling methods, etc.)	[1037]
5.9.	Distributed aggregation and fast fractal clustering approach for SOAP traffic	[63]
5.10.	Traffic-aware clustering scheme for MANET using modified elephant herding optimization algorithm	[1052]

5.3.9. Clustering-based problems in satellite communications

here the following studies on mult0level network architecture can be pointed out

Study 1. Multi-level cluster-based satellite-terrestrial integrated communication [821] as mobile tracking, multi-level clustering, Internet of vehicles, satellite-terrestrial integrated communication: (1) architecture, (2) vehicle communication covered by satellites, (3) multi-level clustering: layer 1: vehicle level clustering, layer 2: infrastructure level clustering, layer 3: satellite-level clustering, and layer 4: space-level clustering.

Study 2. Heterogeneous quantum computing for satellite constellation optimization: solving the weighted k-clique problem [181].

Here single constellation of N satellites are to be dividing into k-sub-constellations, with N and k pre-determined based on availabilty.

Further the goal is to find the assignment of each satellite to a sub-constellation such that the total coverage of a designed Earth region is maximized.

Study 3. Satellite observation scheduling with a novel adaptive simulated annealing algorithm and a dynamic task clustering strategy [1308].

Some clustering studies in satellite communications are listed in Table 5.15.

Table 5.15. Some clustering studies in satellite communications

No.	Some studies of control issues in networks	Source(s)
1.	Multi-level cluster-based satellite-terrestrial integrated communication	[821]
2.	Heterogeneous quantum computing for satellite constellation optimization (solving the weighted k-clique problem	[181]
3.	Satellite observation scheduling with a novel adaptive simulated annealing algorithm (dynamic task clustering strategy)	[1308]

5.3.10. Multidimensional scaling in sensor positioning

Table 5.16 contains a list of basic studies of the using MDS in network node/sensor positioning/localization.

Table 5.16. MDS in network node/sensor positioning/localization

No.	Study	Source(s)
1.	Locatization/positioning in networking:	
1.1.	Plain MDS (connectivity based localization)	[1131]
1.2.	Distributed weighted-multidimensional scaling for node localization in sensor networks	[349]
1.3.	Centralized manifold learning techniques to estimate sensor locations	[1000]
1.4.	Multidimensional scaling framework mobile location using time-of-arrival measurements	[328]
1.5.	Supplement to multidimensional scaling framework for mobile location (modified view)	[313]
1.6.	Multidimensional scaling approach for node localization using received signal strength measurements	[817]
1.7.	Dynamic multidimensional scaling algorithm for 3D mobile localization	[353]
1.8.	Cluster-based multidimensional scaling for irregular cognitive radio networks localization	[1085]
2.	Positioning/localization in WSNs:	
2.1.	Local MDS: Sensor positioning in wireless ad-hoc sensor networks	[636]
2.2.	Efficient weighted multidimensional scaling for WSN localization	[282]
2.3.	Fast and effective multidimensional scaling approach for node localization in WSNs	[751]
2.4.	Multidimensional scaling analysis algorithm of nodes localization based on steepest descent in WSNs	[1390]
2.5.	Distributed weighted multidimensional scaling algorithm for localization in WSNs	[409]
2.6.	Distributed on-line multidimensional scaling for self-localization in WSNs	[920]
2.7.	Multidimensional scaling techniques for RSS-bases WSN localization (review)	[1111]
2.8.	Multidimensional scaling positioning method for mobile station localization in WSNs	[1036]
2.9.	Multidimensional scaling for nodes localization in 3D WSNs	[1189]
2.10.	Multidimensional scaling-based localization techniques (WSNs, IoT)	[1087]

Two main applications of multidimensional scaling (MDS) in communications are examined as follows:

1. Sensor positioning in wireless ad-hoc sensor networks using multidimensional scaling [636].
2. Node localization in sensor networks by distributed weighted-multidimensional scaling [349].

In the sensor localization application of MDS (i.e., mapping of sensor positions in 2D/3D) the following schemes are considered:

Scheme 1.1. Plain MDS [1131].

Here the distance between two connected nodes is defined to be 1. In other cases the distance equals to the number of hops in the shortest path between nodes. The matrix of communication distances between each pair of devices is used by an MDS algorithm to estimate the coordinates of the devices.

Scheme 1.2. Local MDS [636].

Here a local version of MDS is used to compute maps of many local arrangements of nodes.

Scheme 1.3. Manifold learning based MDS [1000].

Here centralized manifold learning techniques are used to estimate sensor locations,

In node localization in sensor networks two schemes are used:

Scheme 2.1. Node localization in sensor networks by distributed weighted-multidimensional scaling (wMDS) [349].

Scheme 2.2. Multidimensional scaling-based localization techniques for WSNs and IoT [1087].

Note the set of used MDS types can be extended.

5.3.11. Additional clustering-based problems

Table 5.17 contains a list of some additional clustering-based problems/studies in communications.

Table 5.17. Some additional clustering-based problems in communications

No.	Study	Source(s)
1.	Clustering-based location in wireless networks	[888]
2.	Cluster-based resource allocation and user association in mmwave femcell networks	[1179]
3.	Clustering-based interference management	[357]
4.	Optimization based on spectral partitioning for node criticality assessment	[127]
5.	Clustering-based content placement in cache networks (using graph-coloring)	[634]
6.	Coordinated multipoint transmission in dense cellular networks (with user-centric adaptive clustering)	[483]
7.	Clustering scheme for vehicular networks using only V2V communications	[1074]
8.	Inter-cluster interference management based on cell-clustering in network MIMO systems	[915]
9.	Self-organizing adaptive clustering for cooperative multipoint transmission	[1291]
10.	Spectrum-aware clustering in cognitive radio networks	[234]
11.	Virtual organization clusters: Self-provisioned clouds on the grid	[930]
12.	Clustering based solving framework for hierarchical resource allocation in hyper-dense small cell networks	[1040]

6. Conclusion

The survey paper addresses some applications of combinatorial clustering engineering approach to communication networking (e.g., design, management/control, maintenance). Basic combinatorial optimization models and heuristics are described. The large list of applied clustering-based problems in communication systems is presented. Applied networked examples illustrated the suggested approach.

It is necessary to note the following:

(i) many parts/components of the survey material have to be extended (including basic combinatorial clustering problems, descriptions of the problems, solving schemes and heuristics, applied examples, bibliography);

(ii) the combinatorial clustering engineering approaches can be applied in other types of networking domains (e.g., social networks, innovation networks, supply chain networks).

The list of prospective future research directions involves the following:

1. examination of new prospective combinatorial clustering methods and their applications in the field of communication systems;

2. studies of clustering approaches based on “near-clique” structures (e.g., quasi-cliques, k-cliques, k-plexes, k-clubs);

3. studies of modularity clustering problems andd methods;

4. special studies of clustering approaches in contemporary information-communication systems (e.g., IoT, cloud computing, FOG computing, Software Defined networks, virtualization in networks, integrated space-air-ground-sea communication system);

5. investigation of interconnections between clustering approaches (frameworks) and families of basic combinatorial optimization problems (e.g., assignment/location/allocation problems, covering problems, spanning problems, scheduling problems, independent set and dominating set problems);

6. wide usage of prospective combinatorial clustering problems (e.g., multicriteira/multiobjective problem, problems under uncertainty, dynamical/multistage problems);

7. design of a special decision support system (DSS) for combinatorial engineering clustering approach and its applications;

8. the structure (architecture) of the material may be interesting and useful as a basic one for many applied domains: two-partite graph based on three parts based on a set of mathematical models, a set of applied problems, and relationship of the elements of the above-mentioned sets; and

9. usage of the combinatorial clustering engineering approaches in CS/engineering education including various student projects (i.e., modeling, applications).

In general this material can be interesting and useful for many readers from various domains (e.g., students, researchers, professors). This material can be used as a ’reference text’ as well.

The author states that there is no conflict of interest.

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