Chapter 4: Big data optimization in electric power systems: A review

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4.1 Introduction

There are different definitions of big data, and among them, the most common definition refers to three or five characteristics, called volume, velocity, variety, value, and veracity from (Laney (2001)). Volume could include Tera Byte, Peta Byte, Exa Byte, and Zetta Byte. Velocity describes how fast the data are retrieved and processed ‘‘Batch or streaming”. Variety describes structured, semi-structured, and unstructured data (Laney, 2001, Zikopoulos and Eaton, 2011). Veracity explains the integrity and disorderliness of data, while value refers to how good is the “value” we derive from analyzing data? (Zicari et al., 2016).

Electrical power systems are networks of components arrayed to supply, transfer, and use electric power. In power system since models are used to predict and characterize operations. However, there is a necessity for powerful optimization algorithms for information processing to learn models as the size increase of data is becoming a global problem to solve large-scale optimization problems. Any optimization problem includes a real function to be maximized or minimized by systematically determination of input values from an allowed set of values. Richness and quantity of large data sets provide the potential to enhance statistical learning performance but require smart models that use the latent low-dimensional structure for effective data separation.

This chapter reviews the most recent scientific articles related to large and big data optimization in power systems. Optimization issues such as logistics in power systems and techniques including nonsmooth, nonconvex, and unconstrained large-scale optimization are presented. After a brief review of big data, scientometric analysis has been applied using keywords of “big data” and “power system.” Besides, keywords analysis, network visualization, journal map, and bibliographic coupling analysis have been done to draw a path on big data works in power system problems. Also, the most common useful techniques in large-scale optimization in power system have been reviewed. At the end of this chapter, metaheuristic techniques in big data optimization are reviewed to show that many efforts have been involved in big data optimization in power system and systematically highlight some perspectives on big data optimization.

4.2 Background

Before starting the discussion about big data optimization, this section reviews the importance of big data projects. Analyzing the big data could release valuable information. Setting up a big data task is a challenge that requires many tasks and processes to be done alongside with data store.

To support a big data-based project, one first needs to analyze the data. There are specific data management tools for storing and analyzing large-scale data. Even in a simple project, there are several steps that must be performed. Figure 4.1 shows these steps that include data preparation, analysis, validation, collaboration, reporting, and access. They are briefed as follows:

- <u>Data preparation</u> is the process of collecting, cleaning, and consolidating data into one file or data table to be used in the analysis.
- <u>Data analysis</u> is the process of inspecting, cleansing, transforming, and modeling data to

discover the useful information, draw conclusions, and support decision-making.

- Data validation is the process of ensuring that data have undergone a kind of cleansing to ensure they have acceptable quality and are correct and useful.
- Data collaboration means data visualization from all available different data sources while getting the data from the right people, in the right format, to be used in making effective decisions.
- Data reporting is the process of collecting and submitting data to authorities augmented with statistics.
- Data access typically refers to software and activities related to store, retrieve, or act on data housed in a database or other repository.

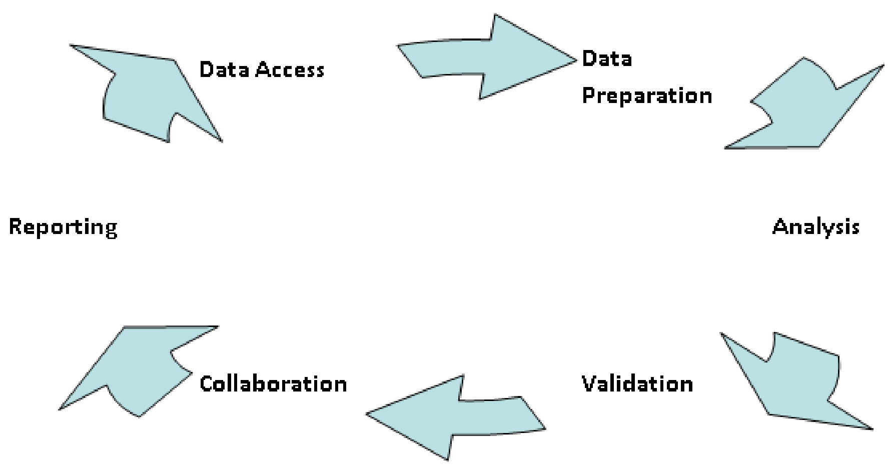

Figure 4.1: Process of data analysis

Big data analysis provides valuable opportunities to support decision-making in several areas, including education, and manufacturing, healthcare. For instance, big data analytics have helped yield healthcare improvements by providing personalized medicine and prescriptive analytics, while in manufacturing big data analysis provides an infrastructure for transparency in the manufacturing industry, which is the ability to unravel uncertainties such as inconsistent component performance and availability. An example of big data in science is the NASA Center for Climate Simulation (NCCS) that stores 32 petabytes of climate observations and simulations on a discover supercomputing cluster. Amazon, eBay, Facebook, and Google are some examples of the application of big data in today's technology. Also, McKinsey Global Institute is known as an entity that applies big data in educational aspects. Table 4.1 presents some areas of big data applications in different fields, additional examples can be found in (Bihl et al., 2016).

Table 4.1: Application of big data

Area	**Scholars**
Healthcare	(Huser and Cimino (2016), O'donoghue and Herbert (2012), Mirkes et al. (2016), Murdoch and Detsky (2013))
Manufacturing	(Lee et al. (2014b), Li et al. (2015), Lee et al. (2015))
Science	(Guide (2013), Brumfiel (2011), Francis (2012), Swan (2013))
Technology	(Tay (2010), Johnson (2010), Sullivan (2015), Layton (2013))
Education	(Manyika et al. (2011), Picciano (2012), West (2012))
Media	(Smith et al. (2012), Xu et al. (2016), Couldry and Turow (2014), Burgess and Bruns (2012))

4.3 Scientometric analysis of big data

Every activity in the 21st century such as financial transactions, research, sales and purchase, security, transport, automobile sectors, internet, and others, requires data. With the advances in technology and fast development of the internet, people observe the extent of data and information that enable access to vast amounts of data in a simple manner. However, this also needs a large amount of data with suitable storage capacity to host them. Nowadays, data manipulation techniques and computational capacities are some of the issues arising from big data, in which the classic technologies are not able to deal with them. Many researchers are working to resolve these problems in various areas such as health, economic, business, physics, and social sectors.

To highlight and show the importance of big data in today's power systems, scientometric technique and social network analysis (SNA) are used in the literature review. Recently, these techniques have become widespread because they facilitate understanding of some dynamical features such as collaboration among scholars (Emrouznejad and Marra (2016), De Stefano et al. (2011), Lee et al. (2014a)). Simply, they are known as strategic intelligence tools for the control of an emerging technology Rotolo et al. (2014).

Scientometric, is a key enabler that observes scientific publications to explore the structure and growth of a specific science using some quantitative measures of scientific information, as the number of scientific articles published in a given period, their citation impact, etc (Rajendran et al., 2011). The main idea is to visualize data on behalf of a principal subject area to signify the whole activities in scientific output. The scientometric mapping technique is used to find the most common keywords that were used in recent research articles. For this aim, the title ‘large-scale power system’ is searched in SCOPUS database which recalled about 1107 scientific articles. Figure 4.2 presents the distribution of these papers from the 1970s.

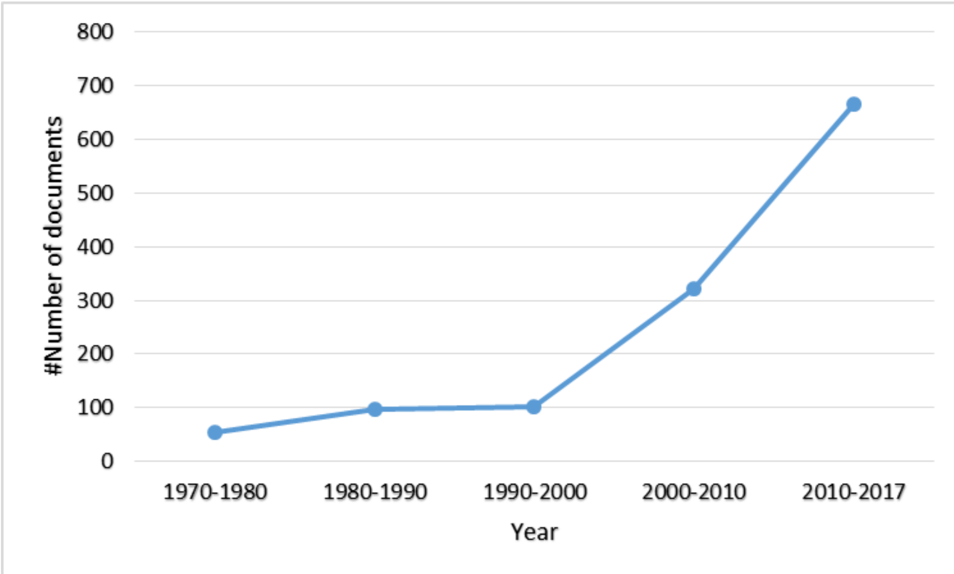

Figure 4.2: A number of publications on ‘Large-scale power system.

Figure 4.3 presents a cognitive map where the size of the node is the equivalent number of publications on the considered term. Links among disciplines are shown by a lie whose density is proportional to the level of which two topics were being used in one article. The color of an item is managed by the cluster to which it belongs.

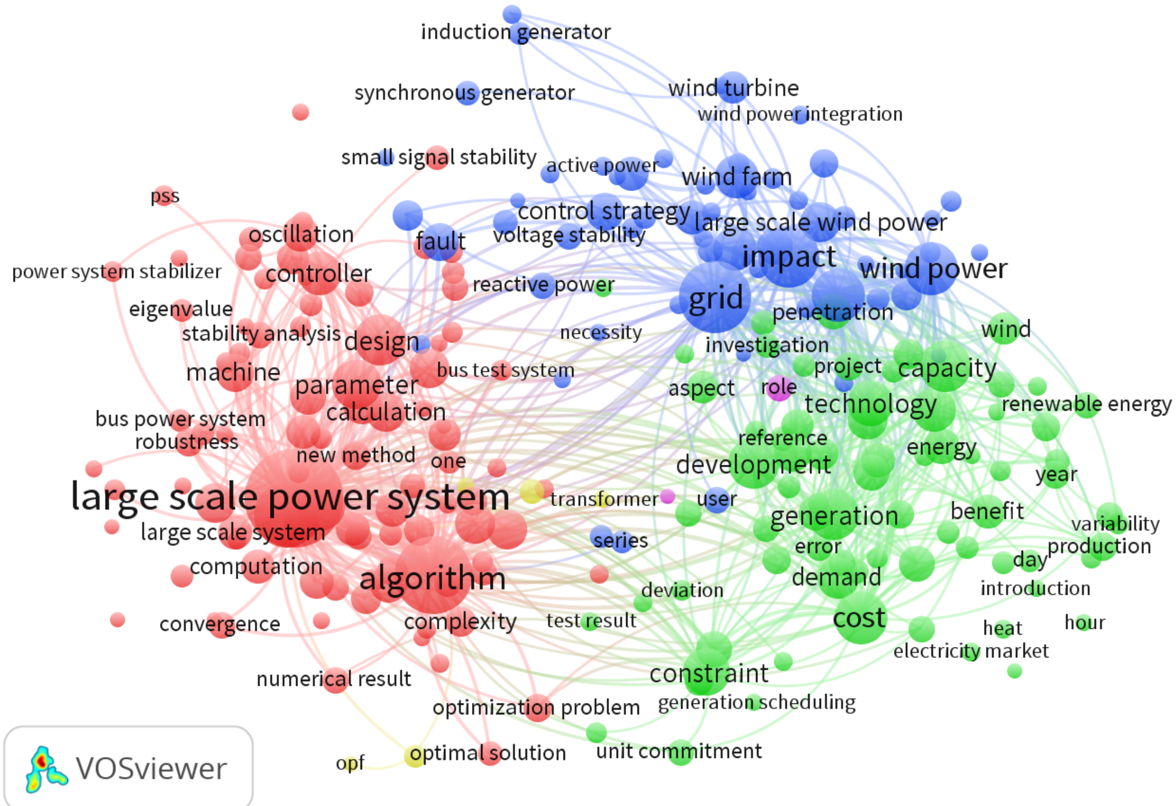

Figure 4.3: Cognitive map (keyword search based on co-occurrences)

The most commonly used keywords (ten keywords) and their number of occurrences have been given in Table 4.2. The objective of keyword analysis is to analyze the terms in a good accuracy. The process mainly depends on brainstorming to find the keywords which still have a high number of searches.

Table 4.2: The most commonly used keywords in big data optimization literature

No.	Keyword	Occurrences
1	Large-scale power system	399
2	Algorithm	248
3	Grid	211
4	Technique	166
5	Impact	152

6	Wind power	119
7	Cost	116
8	Integration	114
9	Capacity	110
10	Development	107

Figure 4.4 presents a different visualization of a country map that indicates collaboration among authors from different countries by lines. Authors from around 101 countries have collaborated in developing articles in big data and power systems. Figure 4.4 shows that China is the most active country in the power system field, then, the USA and Japan are at the second and third stages, respectively. Table 4.3 presents rank of the top five organizations, which have been addressed in affiliations of authors, with respect to the number of documents and citations.

Table 4.3: Rank of the top 5 organizations by number of documents

No.	Organization	Number of documents	Number of citations
1	China Electric Power Research Institute	9	110
2	North China Electric Power University	7	247
3	Tsinghua University	4	36
4	University of Queensland	4	40
5	Brunel University	4	6

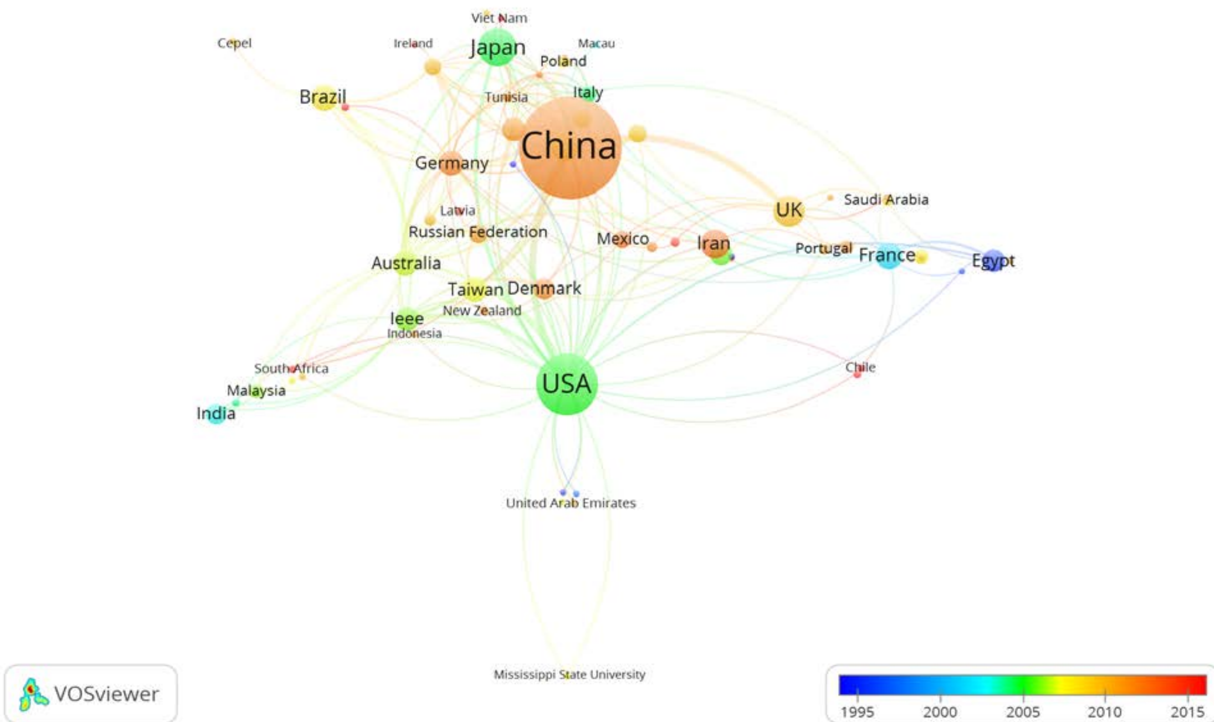

Figure 4.4: Network visualization (collaboration between countries)

Also, collaboration among authors has been analyzed. Figure 4.5 presents co-author collaborations to display the robust and fruitful connections among collaborating researchers. The links across the networks in Figure 4.5 shows the scientific communities involved in research on power systems and large-scale problems.

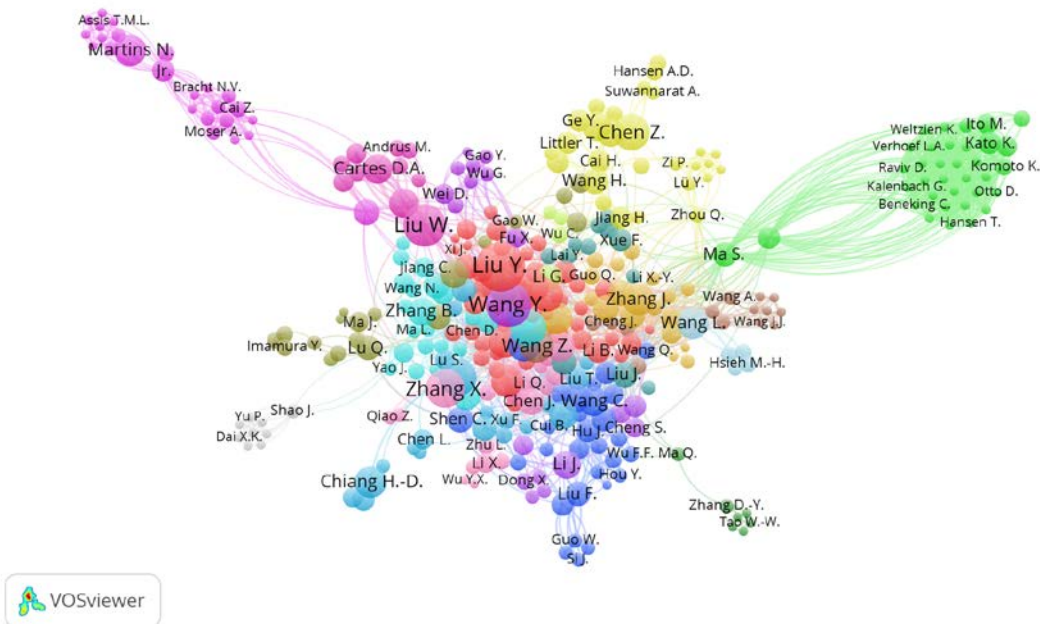

Figure 4.5: Scientific community (co-author) working on the large-scale power system

Figures 4.6 and 4.7 show network visualization and density map of the active journals in power system and large-scale problems based on citation analysis. Figure 4.6 presents the journals aggregated by density. The color shows the density, where the red color indicates a high density of a journal, while the blue color indicates the low-density journals. The right side of Figure 4.7 shows the densest area, occupied by journals dealing with the power system. The most frequent hosting sites are IEEE Transaction on Power System, Applied Mechanics and Material, Power System Protection and Control, Automation of Electric Power System, IEEE Power and Energy Society General Meeting, International Journal of Electrical Power and Energy Systems, and Proceedings of the Chinese Society of Electrical Engineering.

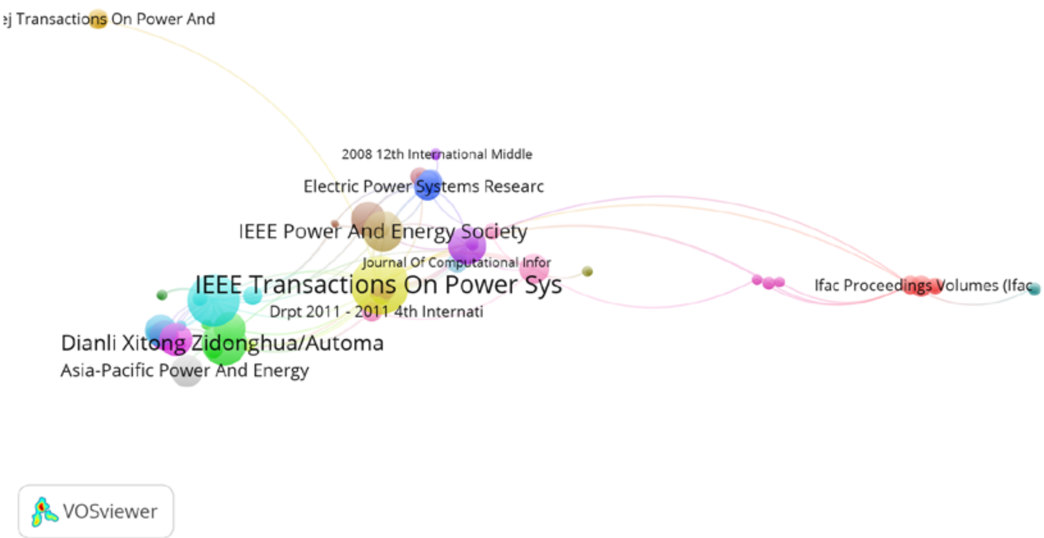

Figure 4.6: Journal map (title) based on citation analysis

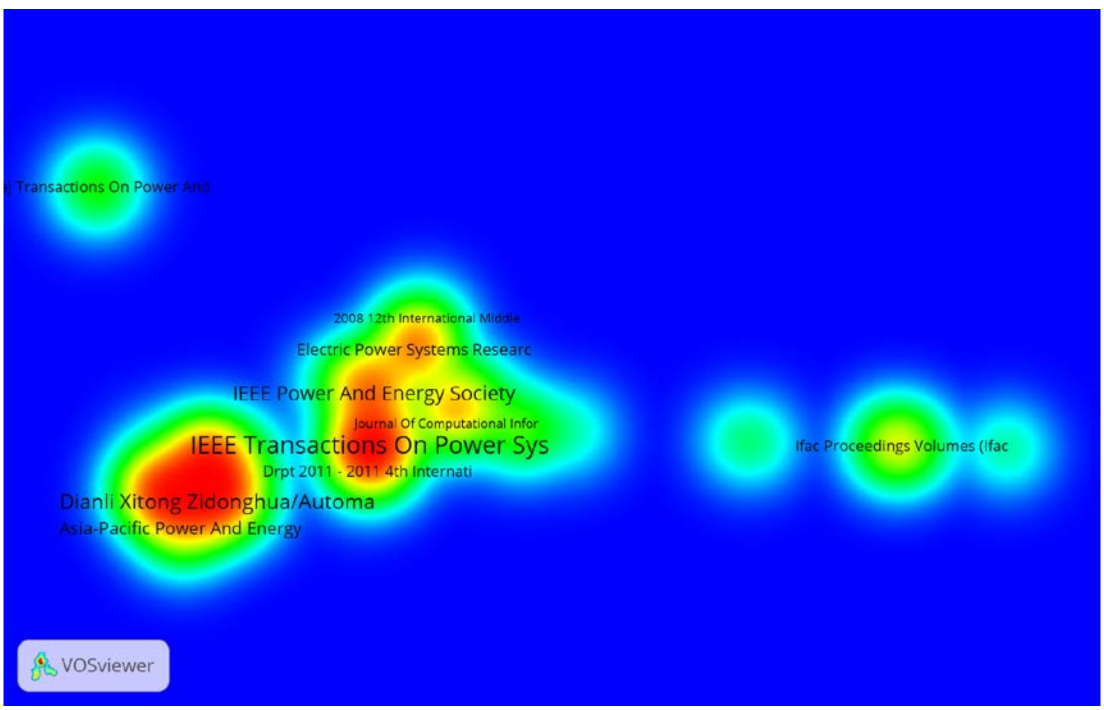

Figure 4.7: Density map (Journal title) based on citation analysis

Figure 4.8 shows different analysis (co-citation) of cited journals which possesses a minimum of ten citations for each source, and this leads to 152 sources with co-citation links.

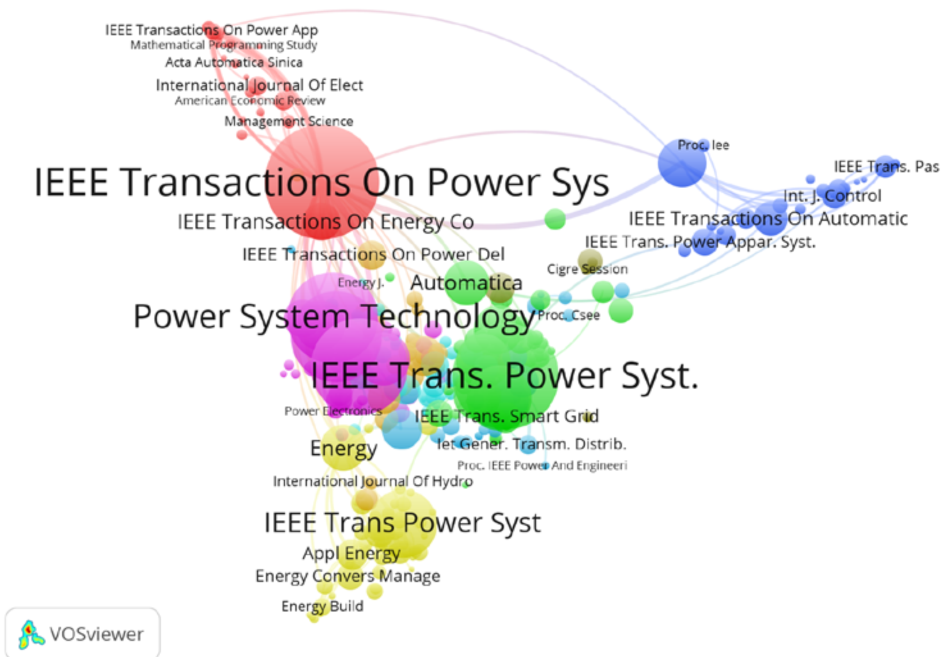

Figure 4.8: Network visualization (co-citation analysis)

4.4 Big data and power systems

There are many large-scale optimization problems in power system, especially in the cases which consider the uncertainty of input parameters (Charwand et al., 2015b, Esmaeel Nezhad et al., 2015, Ahmadi et al., 2013, Charwand et al., 2015a, Ahmadi et al., 2016, Mavalizadeh and Ahmadi, 2014, Sharafi Masouleh et al., 2016). Various researchers, c.f. (Charwand et al., 2015b, Esmaeel Nezhad et al., 2015, Ahmadi et al., 2013, Charwand et al., 2015a), consider the optimal operation of an electrical energy retailers. Ahmadi et al. (2016) proposes a stochastic programing for the optimal operation for a distribution company. Mavalizadeh and Ahmadi (2014) considers emission and security for generation and transmission expansion planning. (Sharafi Masouleh et al., 2016, Ahmadi et al., 2011) use a mixed integer linear model for the optimal operation of hydro generation units. (Moghimi et al., 2013, Ghadikolaei et al., 2012) investigate the effects of distributed energy resources in the short term optimal operation of power systems. (Esmaeily et al., 2017, Aghaei et al., 2015b, Karami et al., 2013, Aghaei et al., 2015a) suggest using a Roulette wheel mechanism and lattice Monte Carlo simulation methods for modeling of uncertainties in hydrothermal scheduling problem. (Charwand et al., 2015b, Esmaeel Nezhad et al., 2015, Ahmadi et al., 2013, Charwand et al., 2015a, Ahmadi et al., 2016, Mavalizadeh and Ahmadi, 2014, Sharafi Masouleh et al., 2016) have many integer variables, for example (Aghaei et al., 2015a) report that the last case study has 3,841,392 variables, 1,610,808 discrete variables, and 4,712,112 equations. This example shows that the number of variables and equations are high. In the following sections, the background of big data in power systems is presented along with applications and the most common approaches in big data optimization in power systems.

4.4.1 Big data optimization

Big data optimization is one of the important issues in big data areas that have been widely arisen with many challenges such as privacy, size of data, and data management (Zicari et al., 2016). Social network science, Machine learning, and biology are instances of many noticeable application fields where it is easy to formulate optimization problems with millions of variables. However, there is a necessity for powerful optimization algorithms for information processing to learn models as the size increase of data is becoming a global problem to solve large-scale optimization problems. Classical optimization algorithms are not planned to measure to cases of this size; new methods are required. Some examples of mathematical optimization in big data include logistics and supply chain issues (Gunasekaran et al., 2017, Papadopoulos et al., 2017, Wu et al., 2017, Kache et al., 2017, Zhao et al., 2017, Brouer et al., 2016), nonconvex optimization (Gong et al., 2016), unconstrained optimization (Babaie-Kafaki, 2016), and nonsmooth optimization (Karmitsa, 2016). Big data optimization is usually taken into account in power systems research like management and scheduling, power dispatch, and energy demand.

4.4.2 Application of big data in power system studies

The use of big data has increased in several ways so that private companies and governments are investing billions of dollars in data management and analysis (Cukier, 2010)). In power systems, data could be gathered from different sources such as renewables like solar and wind energies or other portions of energy technologies such as gas and fuel. In this regard, there are several applications of big data in energy domain that could be surveyed as renewables data use in biomass energy (Paro and Fadigas, 2011), marine energy (MacGillivray et al., 2014), (Wood et al., 2010), and wind energy (Billinton and Gao, 2008), (Kaldellis, 2002), energy consumption (Kung and Wang, 2015), or may consider energy demand response such as power demand (Liu et al. (2013), and storage capacity (Goyena et al. (2009), or could be analyzed as electric vehicles (EVs) (Jiang et al., 2016) such as driving pattern (Wu et al. (2010), energy management (Su and Chow (2012), energy efficiency (Midlam-Mohler et al. (2009), driving range (Rahimi-Eichi et al., 2015), (Lee and Wu, 2015), battery capacity (Shor, 1994), data quality (Zhang et al., 2015), and EVs state (Soares et al., 2015).

Also, there are other challenges in storage and analysis of data, visualization, sharing, etc, (Boyd and Crawford, 2011). It is common to identify trends, spots of problems, and predictive analysis to gain useful information from data. However, it is a big challenge when the problem is faced with big data. So a feature that is necessary for a successful big data analytics system is the need to make the data “over-the-counter” for understanding and using the data satisfactorily. This is especially vital for “high-stakes data” used to make better decisions. Firms which are making plans for big data tend to propose methods that consume less expensive storage, and processing alternatives, as well as tools to enhance data management. However, some of the significant challenges respondents cited to big data implementation, are finding a staff to work in this domain and then training them while adjusting new methodologies for analytics and optimization.

4.5 Optimization techniques used in the big data analysis

Traditional optimization methods could not be used to scale the large data size correctly; thus, new methods are critically needed. Optimization techniques in big data include several issues such as optimization big images, intelligent reduction, optimization based on Hadoop, and mathematical and metaheuristic optimization (Emrouznejad 2016). There are numerous optimization methods that have been applied to power system operations. They are introduced, as follows:

4.5.1 Computational method for large-scale unconstrained optimization

In some big data optimization programming, there are many variables resulting in a need for high memory. One of these applications is called unconstrained optimization which has broad application in engineering, industry, economic, and other fields. Unconstrained optimization also emerges from rewriting of constrained optimization by replacing some penalty terms in objective functions with some constraints. In this way, there is some application of unconstrained optimization method in power system problems (Zhu, 2015). While there are several approaches to dealing with unconstrained optimization, a conjugate gradient method is a useful method to solve large-scale cases (Babaie-Kafaki, 2016). Conjugate gradient techniques were suggested by (Hestenes and Stiefel, 1952) that were used for solving the linear system. Required parameters for Hestenes-Stiefel (HS) Method are introduced as follows:

$$\beta_k^{HS} = \frac{g_{k+1}^T}{d_k^T y_k} \qquad K=0,1,\ldots \qquad (4.1)$$

where d_k is the search direction which is computed by inner products. This direction should be descent direction which means $g_k^T d_k < 0$, and $g_k = \nabla OF(x_k)$ where *OF* is a smooth nonlinear function that needs to be minimized, where $y_k = g_{k+1} - g_k$.

Regarding the mean value- theorem $\exists \zeta \in (0,1)$, thus

$$d_{k+1}^T y_k = d_{k+1}^T (g_{k+1} - g_k) = \alpha_k d_{k+1}^T \nabla^2 F(x_k + \zeta \alpha_k d_k) d_k \qquad (4.2)$$

α_k is a step length that is determined by the line search, and the condition $d_{k+1}^T y_k = 0$ can be considered as a conjugacy condition. Conjugate gradient methods include algorithms that are between Newton and steepest descent methods. Steepest descent method (Cauchy, 1847), Newton method (Sun and Yuan, 2006, Watkins, 2004), conjugate direction method (Babaie-Kafaki, 2016), quasi-newton method (Sun and Yuan, 2006), are also applied for unconstrained optimization problems. Using the Hessian information; the techniques affect the direction of steepest descent. One of the weaknesses of the steepest descent technique was the slow convergence of the algorithm. In this regard, the method only needs the first-order derivatives while the Newton method needs second-order derivative. These methods are broadly used for solving large-scale optimization problems.

4.5.2 Numerical approach for non-smooth large-scale optimization

Definition of smooth functions arises from the first derivative (slope or gradient) at every point. In a graphical view, there is no abrupt in a smooth function of a single variable and also can be plotted as a single continuous, for example, the logistic loss $f(x) = \log\left(1 + \exp\left(-x\right)\right)$ is a smooth function. In contrast, non-differentiable and discontinuous functions are classified as non-smooth functions. Moreover, some functions with first derivatives also called non-differentiable. Graphs of non-differentiable functions may have abrupt bends, e.g. $f(x) = |x|$. These types of optimization are introduced as minimizing or maximizing which are broad in many applications such as economic (Outrata et al., 2013), engineering (Mistakidis and Stavroulakis, 2013), data analysis (Astorino and Fuduli, 2007, Astorino et al., 2008, Äyrämö, 2006), and control problem (Clarke et al., 2008). These problems are mostly large-scale. However, small-scale are also difficult to be solved (Karmitsa, 2016). The Boudle method is one of the techniques which could tackle large-scale non-smooth optimization problem. There are two kinds of the bundle method called, limit memory bundle method (LMBM) and diagonal bundle method (D-bundle). Bundle method has also applied in different power system applications such as uncertainty (Bacaud et al., 2001), scheduling (Zhang et al., 1999, Mezger and de Almeida, 2007), decomposition algorithms (Borghetti et al., 2003, Belloni et al., 2003). Some scholars have presented some works for nonsmooth functions (Attaviriyanupap et al. (2002), (Liu and Cai, 2005), Dotta et al. (2009), Roy et al. (2010)).

4.5.3 Big data in logistics optimization

Logistics refers to actions which occur within the boundaries of single firms and supply chain mentions to networks of organizations which work together and coordinate their activities to deliver a product to market. Levels of the decision in the supply chain as illustrated in Figure 4.9, and include three levels (Schmidt and Wilhelm, 2000). Decisions which determine the fleet size in marine logistics, for example, and facility location and layout belong to the strategic level. The logistics network may be possible to serve vast size of customers up to thousands of customers for or a particular network. Operational level involves vehicle routing through transportation network, loading products, the landing of vessels, while tactical level production schedule and individual services (Brouer et al., 2016). However Seaborn constitutes in the logistics network, around 80% of transportation. In this case, network design problem is a primary planning problem in the logistics network. Regarding the demands which should be transported and selecting ports for servicing to supply chain decision makers wish to draw routes for their career to satisfy requirements of customers.

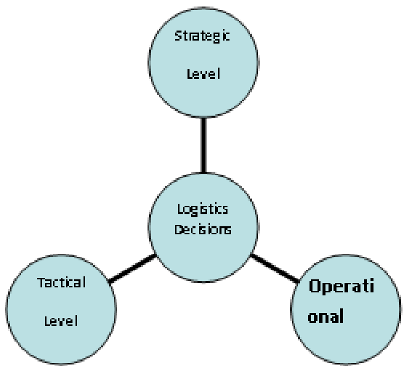

Figure 4.9: Different logistics decisions (Schmidt and Wilhelm, 2000)

Sheu (2008) proposed a novel multi-objective optimization programming model to optimize operations in nuclear power generation (Taiwan nuclear power generation firm) and reduce waste logistics. The author has considered risk reduction in the formulation. The result depicts the improvement of performance from 7.41% to 18.37%, and risks were also reduced by 37.75%.

4.5.4 Big data analytics based on convex and nonconvex optimization

Mathematically, a single objective minimizing (maximizing) optimization could be presented as follows:

$$\begin{aligned} &\min(\max) OF(x) \qquad (4.3) \\ &s.t. g_i(x) \le 0, i = 1, \ldots, m \\ &x \in D \end{aligned}$$

where *x* is called a decision vector and *D* is the feasible region. *OF* is an objective function, and *g* is constrained to function. Convexity condition for *f*, given *D*, holds:

$$OF(\lambda x_1 + (1-\lambda)x_2) \le \lambda OF(x_1) + (1-\lambda)OF(x_2) \quad \forall x1 \ne x2 \in D, \forall \lambda \in [0,1] \qquad (4.4)$$

Moreover, *OF* is strictly convex if the following condition holds:

$$OF(\lambda x_1 + (1-\lambda)x_2) < \lambda OF(x_1) + (1-\lambda)OF(x_2) \quad \forall x1 \neq x2 \in D, \forall \lambda \in [0,1] \tag{4.5}$$

Equation (4.3) is called convex optimization problem if both functions *OF* and *g* are convex. There is a possibility to find a global solution for equation (4.3) if *OF* was convex. However, many real cases face the nonconvex optimization problem. In these cases, researchers try to find the local or global solution (Grossmann, 2013, Mistakidis and Stavroulakis, 2013). One of the relevant optimization problems in power system is known as the economic dispatch (ED). In the ED, the objective is defined allocating power demand among power plants in the most economic situation such that all operational constraints are satisfied. The cost function represents the quadratic fuel cost, and the valve-point effects cost which makes the objective function discontinuous, nonconvex. Selvakumar and Thanushkodi (2007) have applied a new particle swarm optimization (PSO) approach for nonconvex ED problem and suggested a new method in PSO based on the worst position of the particle and integrated it with local random search (LRS) and validated the proposed solution methodology with three economic dispatch tests. Their proposed algorithm shows significant improvement in convergence to the solution. Chaturvedi et al. (2009) used the PSO with time-varying acceleration coefficient in such a way that controls global and local search to achieve the global solution.

In many real applications, there are several objectives to be optimized. Multi-objective optimization usually includes conflict functions, in which improving one function lead to deterioration of the other one, so there is no single solution that can optimize all the functions together. In this case, researchers are looking for Pareto optimal solutions which are good compromising solutions. Equation (4.6) shows a multi-objective problem:

$$Min(Max)\ OF = \{OF_1(x), OF_2(x), ..., OF_n(x)\}, \qquad (4.6)$$
$$s.t.$$
$$x \in D$$

Vector $x \in D$ is called Pareto solution to the problem (4.6) if there is no x^* such that $OF_i(x^*) \leq OF_i(x)$ for any i=1,…,n and $\exists j(1 \leq j \leq n): OF_j(x^*) < OF_j(x)$. If $OF\ (x^*) \leq OF\ (x)$, it is said that x^* is a non-dominated solution. Guo et al. (2016) applied distributed optimization for a large scale non-convex transmission network. The authors applied spectral partitioning approach alongside the distributed optimization method, known as alternating direction method of multipliers (ADMM) to solve a nonconvex problem. In their work, they have shown that the solution found by ADMM is almost close to a local optimum.

4.5.5 Metaheuristic algorithms for big data optimization

Several new challenges have brought with the age of big data. Regarding optimization, researchers may face large-scale size problems, including hundreds, thousands, and even millions of variables. Several techniques have introduced and developed for tackling high dimensional optimization problems. Among them, metaheuristic algorithms are known as efficient algorithms with high computing performance. Several scholars have used metaheuristic algorithms in power system (Chiang, 2016, Camillo et al., 2016, Rajesh et al., 2016, Chen and Chang, 1995, Lee and Yang, 1998). There are significant open research fields and issues for improvement. Among metaheuristic algorithms, evolutionary algorithms are known as a great powerful technique for continuous global optimization. However, increasing the number of variables resulting in deteriorating performance of the algorithm. There is a need for suitable approaches for dealing large scale size problem to find global solutions to the optimization problems. Many scholars have attempted to face this difficulty (Wang et al., 2010, Yan et al., 2004, Chiou, 2007, Lin et al., 2017, Beigvand et al., 2017). An ED is a significant tool in power system operations, which schedules committed generating to meet demand in a point at a minimum cost (Beigvand et al., 2017). Beigvand et al. (2017) proposed hybridization of PSO and the Gravitational Search Algorithm (GSA) for a large-scale, non-convex, non-smooth, nonlinear, and non-continuous combined heat and power dispatch. Summary of (Beigvand et al., 2017) proposed algorithm is presented in Figure 4.10.

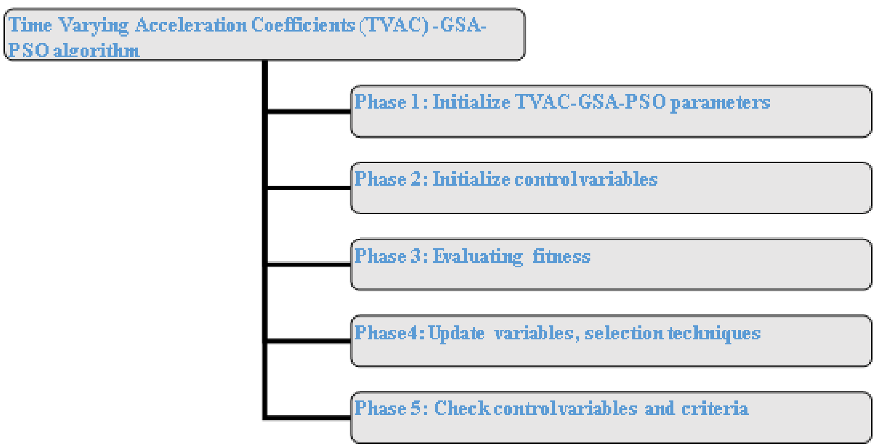

Figure 4.10: Phase classification for Hybrid algorithm

The authors have compared results with several optimization algorithms such as culture PSO (CPSO), modified PSO (MPSO), orthogonal teaching learning-based optimization (OTLBO), and teaching learning-based optimization (TLBO), GSA. Regarding robustness, the suggested method has better performance than other solution optimization methods. Moreover, the results show hybrid algorithm has saved computational time significantly. Quality solution and the convergence speed of the hybrid algorithm possess superior performance than other optimization algorithms. Using of renewable energy has attracted the attention of power system planners across the world. Rajesh et al. (2016) applied differential evolution algorithm in a model of a solar plant to minimize both emission and cost. In the model, the data were gathered from demand and plants, then the model is generated based on assumption. After several studies, the model is developed, and a solution methodology has been selected for the proposed model. A sensitivity analysis was applied to the proposed model, and finally, the future power system model is generated with characteristics such as total cost, capacity additions, emission level.

Naderi et al. (2017) proposed a fuzzy adaptive, comprehensive -learning particle swarm optimization known as FAHCLPSO for the large-scale power dispatch optimization problem. Objective functions for the proposed algorithm include minimizing the active power transmission losses and improving the voltage profile of the system. The authors have validated the performance of their suggested algorithm with three different tests, including IEEE 30-bus, IEEE 118-bus, and IEEE 354-bus test systems. The authors have claimed that the proposed algorithm (FAHCLPSO) was the first applied for optimal reactive power dispatch. They have used fuzzy logic to enhance the searchability of the algorithm.

Table 4.4 and Table 4.5 review classification of metaheuristic methods which have been carried out by scholars. Population-based approaches introduce most techniques and classified by evolutionary computations such as PSO, genetic algorithm (GA), Tabu search (TS), AND ant colony optimization (ACO).

Table 4.4: Literature of metaheuristic classification for power system problems

Metaheuristic								
Population						Trajectory	Implicit	Local search
Naturally inspired								No memory
		Implicit	Explicit	Direct				
Genetic algorithm	Ant colony	Evolutionary programming	Differential evolution	Simulated annealing	PSO	Tabu search	Scatter search	Stochastic local search
Chiang (2005) Gerbex et al. (2001) Walters and Sheble (1993)	Hou et al. (2002) Hou et al. (2003) Niu et al. (2010)	Khatod et al. (2013) Tsai and Hsu (2010) Chung et al. (2010) (Yang et al., 1996)	Lakshminarasimman and Subramanian (2006) Liang et al. (2007) Su and Lee (2003) Sayah and Zehar (2008)	Abido (2000) Zhuang and Galiana (1990) Basu (2005)	Surendra and Parthasarathy (2014) Syahputra and Soesanti (2015) Pan and Das (2016)	Lin et al. (2002) Abido (1999) Mori and Goto (2000)	de Silva et al. (2013) Mori and Shimomugi (2007) Mizutani et al. (2005)	Das and Patvardhan (1998) Das and Patvardhan (2002) Hoos and Stützle (2004)

Table 4.5: Literature of metaheuristic classification for power system problems (continued)

Metaheuristic								
Population						Trajectory	Implicit	Local search
Naturally inspired								No memory
		Implicit	Explicit	Direct				
Genetic algorithm	Ant colony	Evolutionary programming	Differential evolution	Simulated annealing	PSO	Tabu search	Scatter search	Stochastic local search
Panda and Yegireddy (2013) Apribowo and Hadi (2016) Kaur et al. (2017)	Pothiya et al. (2010) Fetanat and Shafipour (2011) Besheer and Adly (2012)	Wu and Ma (1995) Yuryevich and Wong (1999) Lai (1998)	Cai et al. (2008) Shaheen et al. (2011) Wang et al. (2009)	Abido (2000) Romero et al. (1995) Lyden and Haque (2016)	Ahila et al. (2015) Abderrezek et al., (2016) Rouhi and Effatnejad (2015) Park et al. (2005) Niknam (2010) (Park et al., 2003)	Ramírez-Rosado and Domínguez-Navarro (2006) Katsigiannis et al. (2016) Asadpour et al. (2015)	Habibi et al. (2014) Castillo et al. (2007) de Padua et al., (2015)	Hoos (1998) Newton et al. (2013) (Fukuta and Ito (2011))

4.6 Conclusion

The chapter overviewed big data optimization issues in electric power systems. The scientific communities, distribution of publications, and collaboration among researchers around the world have been analyzed. The different types of big data optimization in power system have been discussed. Different types of complicated optimization problems in power systems were discussed. For this aim, factors such as nonlinearity of objective functions, number of variables, Nonsmooth functions were reviewed. One of the most difficulties dealing with these kinds of big data problems relates to the solution approach as addressed.

Because of the ongoing efforts in organizing smart grid infrastructure, the utility business is facing new challenges in dealing with big data and using them to improve decision-making. Big data in the electric power industry can be described in terms of volume, velocity, variety, veracity, value, or all the five terms. Usually, utilities do not handle data using an individual, consistent data management structure which makes ad hoc use of the new decision-making packages needlessly complex. Although analysis of data is accessed through different data, if the data are not timed and spatial, unless they have a common data syntax and semantics for ease of use and if it is not fit for the uniform and common combination of the power system model, such analysis is perhaps not easy to implement. Moreover, one of the most challenging issues in power systems for decision makers arise from optimization problems.

In addition, the chapter shows a significant effort involved in large-scale handling optimization which led to several algorithms, including mathematical optimization and metaheuristic optimizations, which metaheuristic optimizations that have proven to be more accurate, more efficient, and faster than earlier algorithms. Issues such as logistics optimization as well as

Nonsmooth, nonconvex, and unconstrained large-scale optimization are presented. Finally, some metaheuristic methods in large-scale power system optimization are reviewed.

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