Data Mining based Multi-level Aggregate Service Planning for Cloud Manufacturing

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Abstract:

Cloud Manufacturing (CMfg) promotes a dynamic distributed manufacturing environment by connecting the service providers and manages them in a centralized way. Due to the distinct production capabilities, the service providers tend to be delegated services of different granularities. Meanwhile, users of different types may be after services of different granularities. A traditional aggregate production planning method is often incapable of dealing with type of problems. For this reason, a Multi-level Aggregate Service Planning (MASP) methodology is proposed. The MASP service hierarchy is presented, which integrates the services of different granularities into a layered structure. Based on this structure, one of data mining technologies named time series is introduced to provide dynamic forecast for each layer. In this way, MASP can not only deal with the services of multi-granularity, but also meet the requirements of all related service providers irrespective of their manufacturing capabilities. A case study has been carried out, showing how MASP can be applied in a CMfg environment.

Keywords: *Cloud Manufacturing; Production Planning; Service Planning; Service Encapsulation; Data Mining; Time Series*

1 Introduction

Information and Communication Technology (ICT) has become a critical enabler for the manufacturing industry. Due to the breakthrough in novel technologies such as cloud computing and cyber physical systems, manufacturing industry is considering and trialling out the concept of Cloud Manufacturing (CMfg, Xu 2012). Imitating the "pay-as-you-go" service-delivery pattern from cloud computing, a CMfg system is capable of offering on-demand manufacturing services from networked (i.e. cloud-enabled) manufacturing resources (Wang and Xu 2013, Lu et al. 2014). It creates a service-oriented manufacturing environment. Meanwhile, due to the wide implementation of Radio Frequency Identification (RFID) and Internet of Things (IoT) technologies, manufacturing systems now have some advanced characteristics such as dynamic scalability and re-

configurability, and distributive collaboration (Wu et al. 2013). Under this background, advanced service planning and scheduling technologies have become an important subject of study. This paper focuses on the application of Aggregate Service Planning (ASP) for CMfg systems; it stemmed from Aggregate Production Planning (APP) technologies, but with an emphasis on the forecast of service-demand instead of product-demand.

A manufacturing firm in a CMfg environment is regarded as a service provider and is usually coordinated by a cloud platform, through which the services are managed in a centralized way. The service providers have their own capabilities that can be described as services with different granularities. For instance, some firms can offer more complicated and aggregated services such as product assembly (higher-granularity), whereas others may be specialised in products fabrication (lower-granularity). This imposes a serious challenge on the cloud platform to carry out aggregate service planning for all different types of service providers. On the other hand, different types of users may request services of distinct granularities (Wang and Xu, 2013). For example, a customer may request a service for making an end product, whereas an enterprise may request a service for product modules or parts. A traditional APP method therefore does not work for CMfg, as it is built on the consideration of one granularity (mostly the end product), and unable to picture the overall demands in such a complex system. Hence, a Multi-level Aggregate Service Planning (MASP) methodology is proposed to facilitate the management of multi-granularity services in CMfg. The current literature suggests that there is little work done to solve this issue.

The proposed MASP methodology can help guide the production process of service providers irrespective of their capabilities and capacities. MASP is also forecast-based, thus data mining technology is used for acquiring quality prediction results. The two key aspects of the research are service hierarchy and data mining based aggregate service planning.

(i) *Service hierarchy*. Service hierarchy which forms the basis of MASP brings together all the services in a layered structure. To do so, services need to be described in layers according to their granularities. As a service in CMfg is encapsulated as a package of manufacturing tasks (Wang et al. 2014) that can correspond to a manufactured object (e.g. a product or a module), the granularity of a service is considered in accordance with the complexity of the object. For this reason, the modular product structure known as product family, which reflects the complexity of a product and its constituted modules and parts, is introduced to define the service hierarchy.

(ii) *Data mining based aggregate service planning*. CMfg creates a dynamic environment whereby the status of some service providers may change on a regular basis (e.g. via opting in or out of the system). Meanwhile, their shared manufacturing resources may also be changed. MASP is therefore required to make much more dynamic decisions. Thus, data mining supported by IoT technologies is implemented,

which enables the acquisition of real-time production data from service providers, and provides the cloud platform with immediate knowledge for carrying out MASP.

The rest of this paper is organized as follows. Section 2 reviews the related research work in the field. The developed MASP model is explained in section 3. A case study with discussions is given in sections 4. Section 5 concludes the paper with suggested future work.

2 Related Works

2.1 Cloud Manufacturing

Cloud Manufacturing has caught attraction from many researchers around the world since it was first proposed (Li et al. 2010, Xu 2012, Zhang et al. 2014, Wu et al. 2014). Although the concept of CMfg is relatively new, its fundamental characteristics, i.e. virtualizing manufacturing resources as consumable services, has been widely acknowledged and accepted. To realize CMfg, two critical research directions have been identified. One is centred on the formulation of architecture, platform, model and framework to achieve a functional CMfg system (Adamson et al. 2013). In this direction, many service-oriented CMfg systems, such as the 3-layer (e.g. Liu & Jiang 2012), 4-layer (e.g. Xu 2012), 5-layer (e.g. Li et al 2011) and 6-layer (e.g. Xiang & Hu 2012) systems, have been proposed for different requirements and circumstances. The other direction of the research is more service-oriented, such as service encapsulation and resource virtualization, leading to advanced service-oriented manufacturing. This paper is on aggregate service planning for CMfg, hence belongs to the second direction.

2.2 Service Research in Cloud Manufacturing

Service research in CMfg systems is rooted from the service science, which studies the service systems and the interactions between them. Similar to the service system proposed by Spohrer et al. (2008), a CMfg service system can be defined as an opened dynamic system built for configuring, connecting and provisioning of the manufacturing services. To achieve such a system, the technologies such as service encapsulation, matching, planning and scheduling are among some of the most commonly studied subjects.

2.2.1 Service Encapsulation and Matching

Virtualization technologies are frequently applied to achieve service encapsulation. Ding et al. (2012) built a cloud service integration model to virtualize collaborative manufacturing resources. Zhang et al. (2015) presented a service encapsulation model that integrates IoT techniques for CMfg platform to access the virtualized manufacturing machines. These approaches focused on the encapsulation of the manufacturing resources rather than the manufacturing processes (tasks). The methods that considered the servitization of manufacturing processes usually deal with service matching. Semantic and ontology technologies are often used in the proposed systems to achieve this. For instance, Wang et al. (2014) proposed a manufacturing task semantic modelling framework for a CMfg system constituted of task ontology construction approach and task

sub-ontology mapping algorithm. Nevertheless, ontology is a detailed model which may be fit for service matching or more detailed service scheduling. It tends to complicate the tasks of aggregate planning. A much simpler model is therefore needed at the ASP stage.

2.2.2 Service Planning and Scheduling

Based on service encapsulation, service planning and scheduling are much upper-level activities, for which effective technologies need to be developed for the successful execution of production. A service scheduling approach was proposed by Lartigau et al. (2012), in which customer orders are decomposed into tasks for matching the corresponding service providers. Laili et al. (2011) presented an energy adaptive immune genetic algorithm to realise collaborative design task scheduling in CMfg. Based on this research, Laili et al. (2013) later developed a ranking chaos algorithm for a dual scheduling job of cloud service and computing resource in a private cloud, which takes account of interactions between service and infrastructure layers. Most of the articles focus on the ways of service scheduling rather than service planning, let alone any work related to ASP. A system could easily lose the capability of demand-forecast with no consideration of ASP, which is almost certain to hurt the long term benefits. Hence, the study on ASP for CMfg is essential.

2.3 Aggregate Production Planning and Data Mining

When studying ASP, it is necessary to look at APP which is a classic problem. Numerous models have been developed for APP since Holt et al. (1955) first presented a linear decision rule. Wang and Liang (2005) proposed an interactive possibilistic linear programming approach for solving the multi-product production planning problem. Khakdaman et al. (2015) implemented deterministic multi-objective linear programming to solve the supply, process and demand uncertainties for APP problems. As the production environment is increasingly faced with more and more uncertainties, Aliev et al. (2007) maintained that a fuzzy model, instead of stochastic model, can generate satisfied results. Hence, they developed a fuzzy-generic approach for distributed production. Apart from these classic models, APP is also deeply affected by data mining technology which has attracted considerable interest from both academia and industry (Olafsson et al. 2006). Chien et al. (2005) proposed a methodology to forecast cycle time to support APP. Overmeyer et al. (2010) introduced an approach to predict the performance figures of cyclically interlinked production systems. Tirkel (2013) forecasted cycle time in semiconductor manufacturing based on the knowledge discovery system which is also realised by data mining. These methods were developed under the traditional manufacturing conditions, which tended to deal with the APP from the view of product rather than service. Hence, they are not suitable to the service-oriented CMfg environment.

To sum up, the reviewed literature lacks overall consideration of process encapsulation and service granularity for ASP, thus may not facilitate the requirement of CMfg. This paper tries to make improvements in these aspects.

3 Methods

3.1 Service Hierarchy and Multi-level Aggregate Service Planning

In CMfg, the manufacturing process is decomposed of, and encapsulated in, a number of services used to match the manufacturing resources over the cloud. To reduce the complexity in service management because of the diverse customer needs, it is critical for CMfg platforms to create their standardized service architectures, namely service hierarchy, to normalize the task decomposition and service encapsulation. Normalization technologies are frequently used in manufacturing to reduce the complexity of product and production. For example, product family – a standardized platform used to develop a variety of products – has been well recognized as a successful approach to normalize the product design in many industries (e.g. Sanderson & Uzumeri 1995). Process platform constructing the coordination from design to process has been proposed to normalize the complicated production process (Jiao et al. 2007). Based on these theories, considering the interactions between process and service, also imitating the way to formulate a process platform, we establish the service hierarchy on the basis of product family. As shown in Fig. 1, it is a hierarchical architecture mapped from the structure of product family. Each service hierarchy corresponds to a product family, in which a node represents a service (e.g. S1, S2, S3, S4, S5 and S6 in Fig. 1) containing a package of process tasks corresponding to a product or a module. A branch reflects the subordinate relationship between two different services. The granularity of a service depends on its depth in the hierarchy (e.g. Level 1, Level 2 or Level 3 in Fig 1); the deeper, the lower.

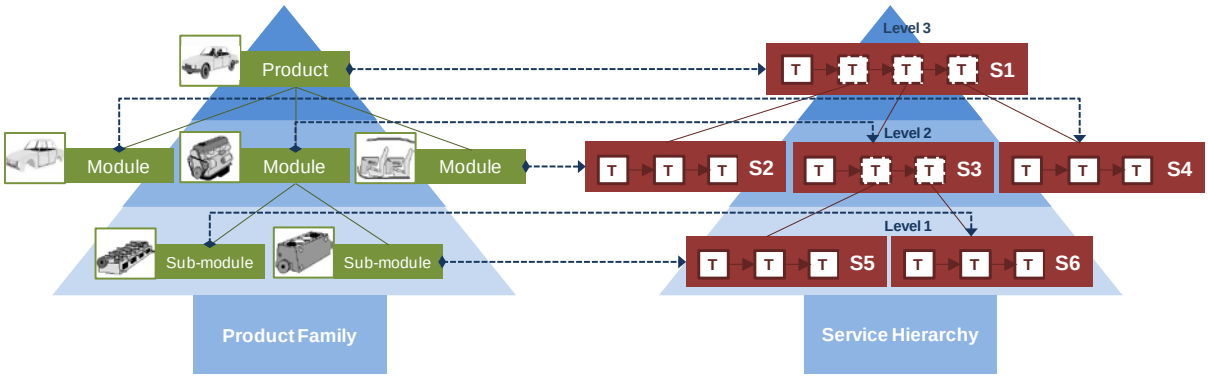

Fig. 1 Mapping between product family and service hierarchy

Cloud platform has the function of integrating the service hierarchy and product family; it helps offer efficient product and service reconfigurations for various demands (Fig. 2). Under this technique architecture, a demand is first translated into an instance of service hierarchy through the product configuration and process servitization stages. Then, different levels of services bonding with the service hierarchy are delegated to the corresponding service providers according to their production capacities and capabilities. For instance (Fig.2), the higher-level services (e.g. assembling the end products, S1) are assigned to Manufacturer 1, while the lower-

level services (e.g. making product modules or sub-modules, S3 and S6) are allocated to Manufacturer 2. It forms a multi-level enterprise collaboration environment.

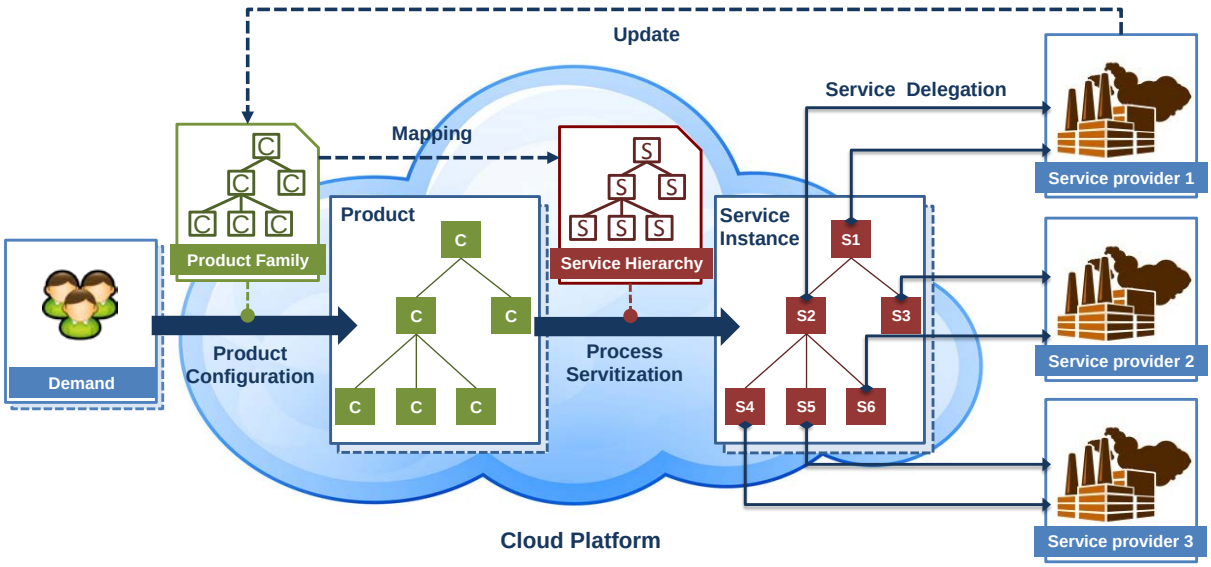

Fig. 2 Process servitization based on product family and service hierarchy

In support of this environment, a MASP methodology is proposed. It is a forecast-based decision made at the macro level, addressing the problem of deciding how many services of each granularity the cloud system should retain. It helps the cloud platform to determine the suitable production quantities and workforce levels of the whole cloud system based on the predicted demand (Nahmias 2001), which can guide the service providers to prepare or maintain their resources as reasonable as possible. Moreover, it gives enough freedom to the development of the following schema such as service scheduling.

MASP considers the production quantities of aggregate units rather than the specific service items. In general, an aggregate unit represents a series of services sharing similar granularities and due dates, which can be aggregately reflected by the service levels in service hierarchy. For this reason, the services in the same level are treated as an identical aggregate unit. By this means, the amount of different aggregate units is equal to the number of service levels. Based on this, MASP is defined as a methodology to deicide service quantities by service levels and time periods.

With the results of MASP, the production quantities of all service providers can be predetermined, regardless of their capabilities and capacities. Table 1 presents a facile way to realize this. Take the service hierarchy of a product for example, in which the services are divided into three levels (Level-1, Level-2 and Level-3). The MASP result is 100 units per year for level-1 service, and 300 and 500 units per year for level-2 and level-3 services, respectively. According to this result, considering the production capabilities and capacities of the involved service providers, their production quantities can be determined. Service provider “A” is capable of fulfilling both Level-1 and Level-2’s services, and the production capacity is estimated as either 150 units of Level-1 per year or 300 units of Level-2 per year. Hence, the production quantities for Level-1 and Level-2 can

be set as both 100 units per year for “A” to utilize the full capacity. In a similar way, the production quantities for service provider “B” and “C” can also be obtained. It is clear that the cloud platform can manage the productions of service providers in a centralized but efficient way due to the consideration of service granularity.

Table 1 Determination of production quantities based on MASP (units per year)

Service Provider	**Production Quantity/Production Capacity**		
	Level-1 Service	**Level-2 Service**	**Level-3 Service**
A	100/150	100/300	-
B	-	200/200	0/400
C	-	-	500/600
MASP Result	100	300	500

3.2 Data Mining based Aggregate Service Planning

MASP is forecast-based. With the support of IoT technologies, the real-time production data can be acquired from the service providers, by which the cloud platform can picture the overall production status to make considerable plans. In this paper, the result of MASP is mined from the historical data which records the due date (finished date) for each service. First of all, the data model is defined. We assume that a demand (an order) be represented as a specific service tree derived from the service hierarchy. As each service has a due date, shared with the same structure of the service tree, a date tree can be formulated; it forms the basic element of the data model. Suppose a set of date trees $O=\{O_i \mid i=1,2,\ldots,I\}$ where O_i is the i-th date tree defined as $\{S_{ijk} \mid j=1,2,\ldots,J_i; k=1,2,\ldots,K_{ij}\}$, in which S_{ijk} represents the due date of the k-th service in j-th level; J_i is the depth of O_i; and K_{ij} is the total amount of services in j-th level. According to J_i, the depth of the tree set O can be obtained as $N=max\{J_i \mid i=1,2,\ldots,I\}$, which means that O has N service levels. Then, as MASP considers the services in the same level as the same aggregate unit, all the nodes ($\{S_{ijk}\}$) should be separated into N groups that corresponds to N levels (Fig. 3). The grouping result is shown as $O=\{G_n \mid n=1,2,\ldots,N\}$, where G_n is the set of nodes in the n-th level, and $G_n=\{S_{ijk} \mid j=n\}$. Thus, G_n is the final processed data set (data model) used for data mining, and each group (service level) is treated separately. Finally, since the service due dates ($\{S_{ijk}\}$) are past discrete values and are usually almost equally spaced because of the impact of production cycle, time series methodology is applied to each service level to forecast the service quantities by time period.

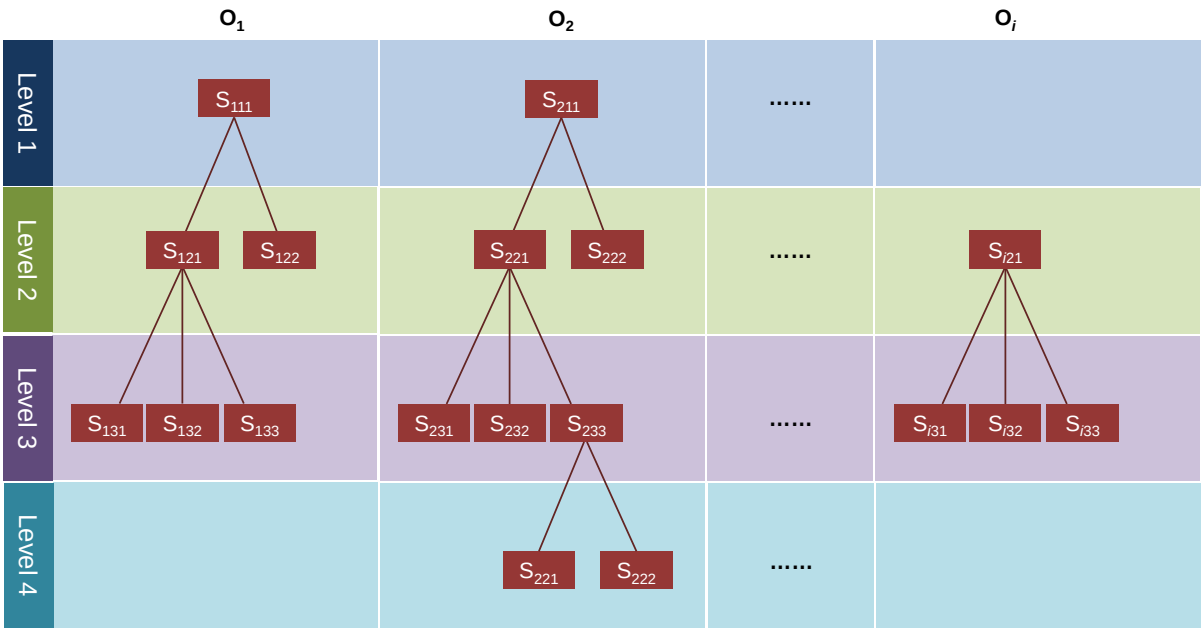

Fig. 3 The layering of the date trees

Time series modelling is a popular method applied in many areas such as economics, engineering and business. The main idea is to collect and carefully analyze the past data in order to find out the most appropriate mathematical model to describe the underlying structure of practical problems. Then, the model could be used to predict the trend of the real issues in the short future. This is very attractive because it could provide a valuable direction for our service plan. In our case, we are interested in knowing how many services we should process in each year or month or even week to avoid too much stock while satisfying customers' demand.

A time series is a sequcence of data typically observed over a period of continuous time. Let X_t be the single observational value evaluated at time point t, where $t \in \{1, 2, ..., T\}$ and T is the number of observations we have got; the spacing between time point t and $t+1$ could be one day, one minute, one week and etc. Take the nth service level for example, X_t corresponds to S_{ink}, and $T = \sum_{i=1}^{I} K_{in}$. If each observation of a time series is a vector including more than one value it is termed as multivariate, otherwise univariate. For example, if the quantity of services in the same level is recoreded every two weeks from the beginning of year 2014 to the end of 2016, the data we have obtained could be regarded as a univariate time series and used to forecast the approximate service quantity at the beginning of 2017. A time series generally comprises four parts: trend, cyclical, seasonal and irregular components. It is obvious to get the meanings and for some details (Adhikari and Agrawal 2013).

After collecting the observational data, the selection of a proper stochastic model is quite important because it might directly influence the accuracy of the result. Using the literature in this filed, we can find many time series models divided into two groups by the fact that whether the observational value at present or in the

future has a linear relationship with the previous data or not. Among all the models, Autoregressive (AR) and Moving Average (MA) models are widely used and their combinations Autoregressive Moving Average (ARMA) and Aoturegressive Integrated Moving Average (ARIMA) models are also applied in many practical problems. In this research, we focus on the linear model ARMA because of its convenience and simplicity without losing the accuracy compared with other ones.

The general form of ARMA model was proposed by Peter Whittle in 1951 and this model was further enhanced by some scholars later. The model ARMA (p, q) has two parameters p and q, and the formula for this model could be written as:

$$X(t) = c + \varepsilon_t + (\varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p}) + (\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}) \quad (1)$$

where φ_i, θ_j are model parameters and ε_k is white noise. For more details about ARMA and some other models, the readers are referred to the paper by Adhikari and Agrawal (2013). In this paper, software R is used to solve the problem and the package 'forecast' provides many convenient tools. It can be more relaxed about choosing a suitable model because some functions in the package can help select the most appropriate one according to the original time series data.

Finally, after selecting and using a model to make a prediction, we need to know the performance of the model we choose, so it is indispensable to know some knowledge about how to evaluate the bias. In the present, many criteria are available and some will be listed and briefly explained hereafter. Note that x_i is the actual value; p_i is the predicted value; $e_i = x_i - p_i$ is the prediction bias and n is the number of predicted values. For these measurements, we can choose any one to judge the performance of our models as all of them have advantages and disadvantages, respectively. In practical situations, if one hopes know the direction of error, MFE should be used to evaluate our methods; if one is interested in the percentage of overall error, MPE is better.

Table 2 Prediction bias measurements

Name	Formula	Properties
MFE	$MFE = \frac{1}{n}\sum_{t=1}^{n} e_t$	- Show the direction of error - Should be zero for a good forecast
MAE	$MAE = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$	- Show the magnitude of overall error - Provides no idea about error direction
MPE	$MPE = \frac{1}{n}\sum_{t=1}^{n} \frac{e_t}{y_t} \times 100$	- Gives the percentage of overall error - Independent from the scale of measurement

4 Case Study and Discussion

A manufacturing firm that operates on its private platform to manage its branch factories and suppliers is selected as an example. IoT technologies have been well implemented in this company; hence the data generated through the production is automatically recorded with accuracy, and is used to forecast the future service

demand. We choose 6 years' production data of a product (2008 – 2014) for the study. There are 1,048,576 records, and each record embraces a bunch of production information, such as the chosen data titled with Component Name (A), Parents Name (B), Service Provider (C), Production Quantity (D) and Due Date (E) listed in Fig. 4.

	A	B	C	D	E
1	**Component Name**	**Parents Name**	**Service Provider**	**Production Quantity**	**Due Date**
2	TM3452.01.01-01	TM3452.01.01	12	1	20/04/2008
3	TM3452.01.01-02	TM3452.01.01	18	1	20/04/2008
4	TM3452.01.01-03	TM3452.01.01	18	1	20/04/2008
5	TM3552.01.01-01	TM3452.01.01	12	1	20/04/2008
6	TM3552.01.01-02	TM3452.01.01	12	1	20/04/2008
7	TM3552.01.01-03	TM3452.01.01	12	1	20/04/2008
8	HN-S89-62-3	TM3452.01.01	17	6	20/04/2008
9	TM3552.01.01-03S	TM3452.01.01	17	1	20/04/2008

Fig. 4 Example of used production data

All the data is collected in .xlsx format. Software R is used to get the tendency and distribution of production from the acquired data as it is an efficient and convenient tool for data analysis. Based on the parent-child relationships between different components (services), indicated by the data of columns A and B in Fig. 4, the service hierarchy is established in which the services are divided into 5 levels. The MASP results are analyzed separately according to these levels as shown in Fig. 5.

From the results shown in Fig. 5, we can get the distribution of the production in the past as well as the predicted quantities of the latest 12 months (2014 - 2015) using the observational data. Associated with them are the 95% lower and upper bounds of the forecasts. Theoretically, if the real observed values lie between the two bounds of the predictions, we can say that it is a fairly safe bet to trust the forecasts. In addition, comparing the predicted production quantity between the five levels, we can find that it is reduced with the increasing of the service level, which is in line with the product structure (a tree), and reflects the structure of service hierarchy (pyramid). It proves the vaildity of the formualtion of service levels.

Furthermore, in order to check the accuracy of the model in the aspect of forecast, we reserve the data of the last twelve months and then use the model choosen to forecast the values and then compare the two groups of data to see the performance of our model. As shwon in Fig. 6, except for the only one or two extreme points, all the other predicted values are quite close to the actual quantities. It is acceptable because it is unrealistic to get results that are almost the same as the actual ones. Using the forecast performance measure, the mean forecast errors (MFEs, see Table 2) for the five levels from level 1 to level 5 are 1760.314, -1412.781, -39.612, -8.205 and 0.647, respectively. As the order of magnitude of the production for each level (Fig. 6) is much greater than the corresponding MFE, i.e. 100000 vs 1760.314 , 40000 vs -1412.781, 7000 vs -39.612, 600 vs -8.205, 60 vs 0.647, we could conclude that the forecasts are credible.

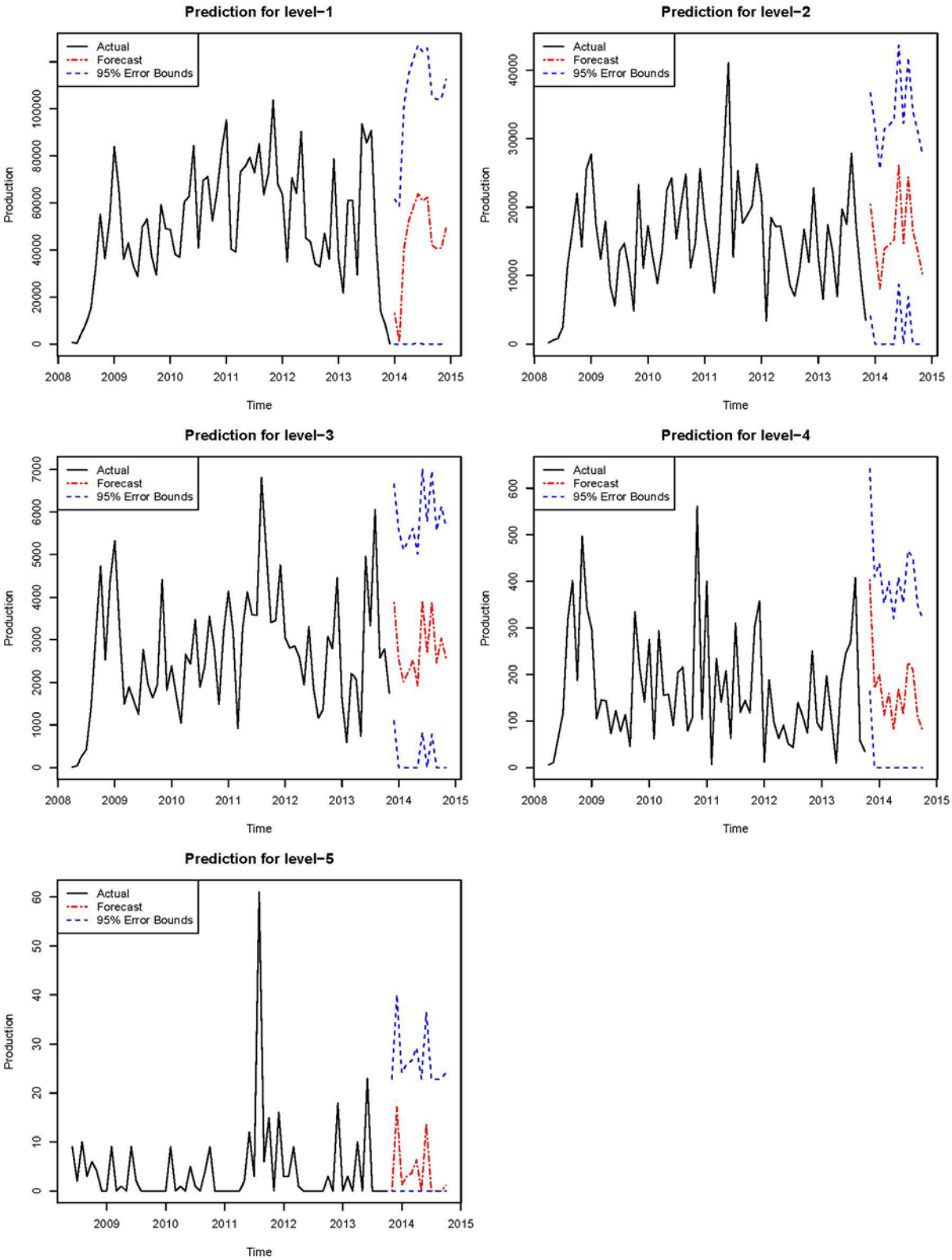

Fig. 5 The forecasts of service quantity by service level and time period

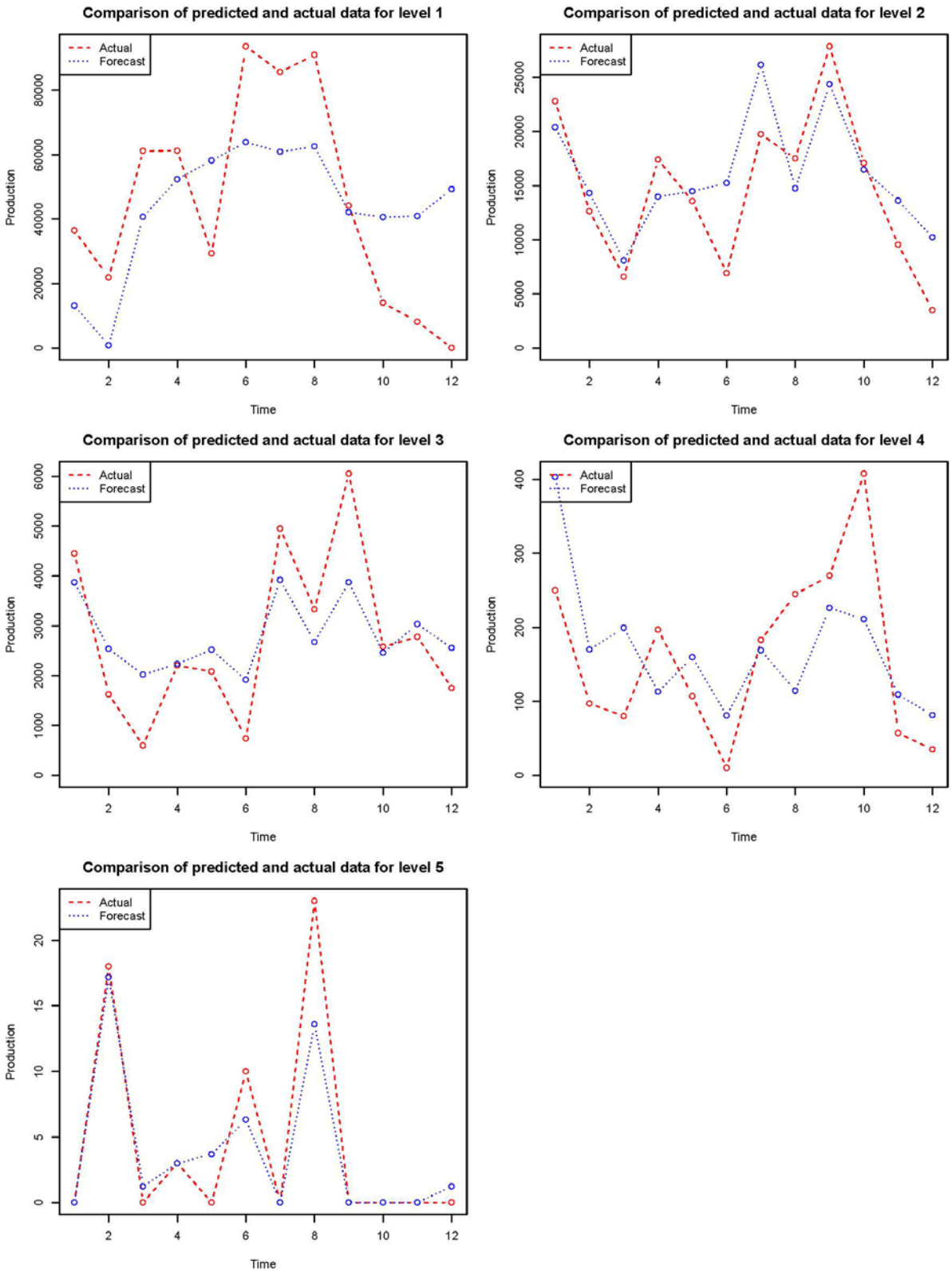

Fig. 6 Performance of the prediction

5 Conclusions

This paper proposed a multi-level aggregate service planning approach for cloud manufacturing to satsify all service providers irrespective of their production capabilities and capacities. Multi-level aggregate service planning uses the service hierarchy to deal with the service with different granularities and applies data mining technology (time serises) to forecast the future demands. As the prediction is based on the real-time production data supported by IoT technology, Multi-level aggregate service planning methodology can be carried out automatically to adapt to the dynamic production fluctuations in a cloud manufacturing environment. The case study demonstrated that the method can be applied to a generic business and the forecast results are credible.

Multi-level aggregate service planning still has some limitations. For example, as the service level is defined based on the manufacturing complexity, it requires the module at the same depth of the product family to be designed within similar complexity (e.g. similar processing time) to ensure the services of the same level can be treated as the identical aggregate unit. This however has the potential to promoting new principles for product modular design.

6 Acknowledge

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