The Application of Artificial Intelligence in PPC: A Case Study

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Abstract

Industry 4.0 has increased the research attention to apply artificial intelligence (AI) into production planning and control (PPC). The use of artificial intelligence in PPC for SMEs have in the past received mix reactions from researchers. This paper aims to explore this gap through a case study to review a Decision Support System (DSS) developed by integrating knowledge-based algorithm with a Simplified Drum Buffer Rope based PPC. Based on recent research development on application of Machine Learning (ML) in PPC, the possible activity areas where ML could potentially be further explored in the current DSS system is proposed.

Keywords: Reactive Scheduling, Production Planning and Control, S-DBR

Introduction

Over the years, researchers and practitioners have proposed various production planning and control (PPC) approaches to improve the performance of production system. Given the uncertainties in production environment, the main challenge to PPC approaches is to generate a practical production plan that is feasible to *execute* (Schragenheim, 2010:213; Wiendahl et al. 2005).

In addition to practicality issues which arises from the operational perspective, PPC is also crucial from the strategic perspective. With the emphasis of alignment between supply chain/operations management strategy and marketing strategy (Fisher, 1997; Stratton, 2018), PPC has evolved into a Decision Support System (DSS) (McKay and Black, 2007). To effectively support DSS, PPC in MTO environment must explicitly include customer enquiry stage into its planning horizon (Hendry and Kingsman, 1991; Stevenson et al., 2005).

With the recent increased research attention in Industry 4.0, the applicability of artificial intelligence (AI), such as machine learning (ML) in PPC has received increased attention (Cadavid et al., 2020; Mezzegori et al., 2019; Priore et al., 2014). The concern where organisations blindly copy a best practice or trend to improve production performance has been highlighted by researchers (Sousa and Voss, 2008). The complexity and sophistication associated with AI in PPC could have possibly reduced its adoption by practitioners in SMEs (Hendry and Kingman, 1989; Tenhiala, 2011). Given that SMEs are characterised by limited resources, the objective of this paper is to review and explore the practicality of AI in PPC for SMEs in MTO environment.

The remainder of this paper is structured as follows. PPC approaches towards uncertainties will firstly be reviewed. This is followed by reviewing the potential use of AI, (i.e. machine learning) in PPC. A case study is presented to illustrate the successful integration of AI algorithm with S-DBR algorithm, followed by a discussion on potential enhancement using machine learning algorithm.

PPC and Uncertainties

PPC approaches to improved production include simulation models, analytical models, heuristic, and artificial intelligence. Details on these approaches have been reviewed by researchers such as Aytug et al. (1994) and Priore et al. (2006). Underpinning these PPC approaches are different inherent assumptions concerning uncertainties in production environment (Aytug et al., 2005).

The traditional PPC approaches view *planning* as a mere mathematical problem, static in nature, and able to be modelled into algorithms (Deblaere et al., 2007; Pinedo, 2008). Once planned, it is assumed to be executable with full adherence. The development in technology (such as in big data and artificial intelligence) has propelled the use of sophisticated algorithm to model uncertainties. These *predictive* approaches are potentially suitable only in tightly controlled and integrated automation environments where uncertainties are relatively low.

The reliance on *predictive* approaches is deemed impractical in dynamic production environment such as Engineering-to-Order (ETO) and Make-to-Order (MTO) where *reactive* approaches are advocated (Aytug et al., 2005; Szelke and Kerr, 1994). Such approaches require PPC to react dynamically to real time events: resource-related and job-related (Ouelhadj and Petrovic, 2008). Resource-related events include machine breakdown, unavailability of personnel due to illness, shortage in raw materials, etc. Job-related events include change in due date, cancellation, processing time, etc. *Reactive* approaches are further categorised into completely reactive, predictive-reactive and robust proactive. Detailed reviews can be found in Aytug et al. (2005), Oelhadj and Petrovic (2009) and Priore et al. (2014).

Completely reactive approaches do not generate a firm schedule in advance. Rather, they are based on resource and job-related attributes, such as priority dispatching rules, used to determine the next job to be processed. This approach involves less sophisticated computational algorithms and intuitive rules, easily understood by users (Aytug et al., 2005; Waschneck et al., 2016). However, these myopic dispatch rules are criticised for being sub-optimal within a wider production system. Attempts to align dispatching rules with the organisation’s wider objectives have been made through AI algorithms. This includes empirical work by Petroni and Rizzi (2002) which uses fuzzy logic methodology to evaluate and select the best dispatch rules based on organisation objectives. Other reported methodologies include decision trees (Piramuthu et al., 1991), neural networks (Chen and Yih, 1996), genetic learning (Aytug et al., 1994), iterative simulation (Kunatnoglu and Sabuncuoglu, 2001), etc.

A robust proactive approach is the opposite of reactive and attempts to create a schedule which can accommodate dynamic environments. These approaches utilise the concept of a buffer to dampen the effect of uncertainty. For example, buffer time by Mehta and Uzsoy (1999) and buffer capacity in the form of under-capacity planning by Horiguchi et al. (2001).

The third category: predictive-reactive scheduling is most commonly used in dynamic scheduling (Ouelhadj and Petrovic, 2009). Conceptually, it inherits the benefits of both prior discussed reactive approaches. The downside is the sophistication in algorithm and the turn-around time of rescheduling. To increase feasibility, researchers have limited the scope to reschedule. These range from the simplest method of right-shift rescheduling, the more practical schedule repair, and the complete regeneration (Viera et al., 2003). Although complete regeneration is theoretically desirable as it provides an optimal solution, the immense computation times makes it impractical. Ouelhadj and Petrovic (2009) cautioned against frequent schedule regeneration as it might increase system nervousness and discontinuity to shop floor operation. With AI developments (such as big data availability and machine learning algorithms). , attention has been directed to evaluate the theory-practice gap for such solutions. A detailed review of the past ten years' achievements is conducted by Priore et al. (2014). *Figure 1* attempts to represent the PPC approaches discussed in this section in a continuum of planning and execution.

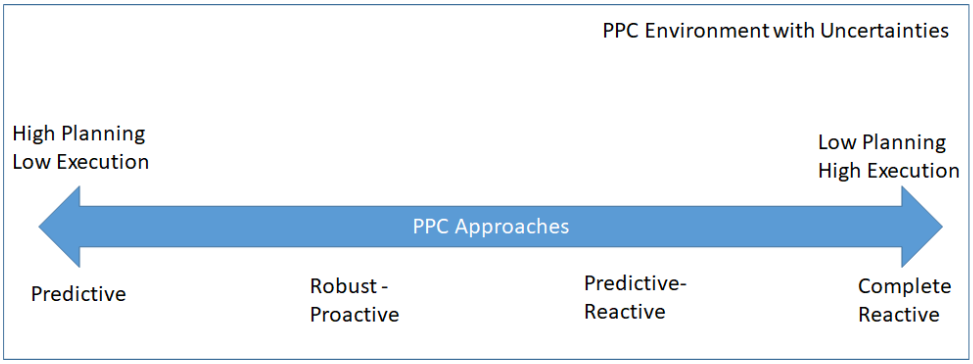

Figure 1: Representation of PPC Approaches in Continuum of Planning and Execution

AI in PPC

The use of AI in PPC has been explored since the early 80s where it is also referred to as knowledge-based systems or expert systems (ES) (Aytug et al. 1994; Kanet and Adelsberger, 1987). According to Bensana et al. (1986), there are two types of PPC related knowledge: (i) the theoretical and empirical knowledge on PPC; and (ii) the practical knowledge of the shopfloor, where the source in both types is human experts. Through AI, the thinking process and decision-making process of human experts are captured as idiosyncratic knowledge. This codified knowledge is built alongside inference mechanisms to mimic human decision making (Metaxiotis et al., 2002).

Although AI is better than the traditional mathematical representation in dealing with uncertainties, concerns have been raised regarding how fast the knowledge database can be updated (Fox and Smith, 1984; Hendry and Kingsman, 1989). The applicability of AI in PPC in a dynamic production environment depends on the learning capability and capacity exhibited (Nakasuka and Yoshida, 1992).

With the advancement in AI, the term now includes analytics, big data, and the use of computers (instead of a human) in problem solving (Olsen and Tomlin, 2020). The advancement in learning algorithms, such as machine learning and the availability of real-time data, creates a pathway towards an active learning PPC (Arnott and Pervan, 2014; Aytug et al., 1994; Misic and Perakis, 2020; Weichert et al, 2019). The knowledge learnt comes from data sources, including management data (e.g. ERP, CRM), equipment data through IoT (Internet of Things) technologies, user data (from ecommerce and social media platforms), product data through IoT (such as product performance, usage related), public data (available through government) and artificial data (generated through simulation) (Tao et al., 2018; Cadavid et al., 2020). Although this could potentially improve production performance, Priore et al. (2006) cautioned against the potential pitfalls due to the uncertainty of the production environment.

In machine learning, problems are solved by using previously acquired knowledge in solving similar problems. To acquire knowledge, machine learning algorithms will learn through past knowledge, known as training examples. Attributes are used to define each example and the solution to each example is part of the attributes, known as class. A review on the development machine learning in PPC by Priorie et al. (2014) categorised learning approaches into inductive learning, neural networks (NN), case-based reasoning (CBR), support vector machines (SVMs), reinforcement learning, mixed approaches and others. The review by Cadavid et al. (2020) took a step further by reviewing the activity areas where machine learning has been reportedly used since 2010. These activities are (i) Data acquisition, (ii) Data exploration, (iii) Data cleaning and formatting, (iv) Feature selection, (v) Feature extraction, (vi) Feature transformation, (vii) Hyperparameter tuning and architecture design, (viii) Model training, validation, testing and assessment, (ix) Model comparison and selection, (x) Contextualised analysis or application, and (xi) Model update. It was reported that the proposed application of machine learning in PPC has mainly centred around model development and assessment, with less than half related to contextualised analysis. The low usage of machine learning in data acquisition and exploration related activities raises concerns over the integration of PPC with the Internet of things (IoT) technologies in obtaining real-time data regarding the manufacturing system status. The least reported activities in the (ix) Model update shows a lack of research in adapting models to the dynamic manufacturing environment. To address this need this paper explores how AI could potentially be applicable to SMEs using a case study.

Case Study: Phase One

The SME case company: Company A, is a planters and bins manufacturer. The manufacturing process utilises rotary moulding and is labour intensive in a Make-To-Order environment. The company intends to improve its competitiveness in the market by digitising its manufacturing process. An incremental change approach is adopted in two phases. Phase one is to design and implement a PPC, followed by exploring the potential use of AI in phase 2. The following section will introduce the first phase of this project, followed by a discussion regarding the second phase.

Using a *reactive* approach, the PPC was designed and implemented using the Theory of Constraints (TOC) based Simplified Drum-Buffer-Rope (S-DBR). Details of S-DBR can be found in Schragenheim and Dettmer (2000) and Schragenheim et al. (2009). S-DBR consists of three pillars: constraints management (CM), load management (LM) and buffer management (BM). CM adopts a systemic approach acknowledging system throughput is dictated by the constraint within a system. In S-DBR, the market is viewed as the ultimate constraint. Company operations and resources are to be aligned and subordinated to support this constraint. In the context of MTO environment, the alignment is to provide customers with feasible due dates that corresponds to the *planning* and *execution* in PPC. To effectively align *planning* and *execution*, S-DBR obtains real-time data on the system status through the other two pillars: LM and BM.

In LM, planned load (PL) is used to monitor the load of internal resources. Instead of monitoring all resources, only resources which potentially will become internal constraint are monitored. These resources are called critical capacity resource (CCR). PL is the total load for all firm orders on CCR. It provides a means to proactively validate CCR capacity against market demand in the planning horizon. PL is also used to quote feasible delivery date to customers. As shown in *Figure 2*, with the assumption that position of CCR is in the middle section of the production process, feasible delivery date is determined by adding one half production buffer (PB) to the earliest available date of CCR. A factor is multiplied to the PB to represent the relative position of CCR in the production route (Lee et al., 2010). S-DBR explicitly acknowledges the existence of uncertainties in manufacturing environments by adding buffer time to the production touch time. The sum of production touch time and buffer time is known as PB. The amount of buffer time added is to allow orders to complete in around half of the PB, the yellow zone in Buffer Management (BM). This allows time for expediting if an order enters the red zone.

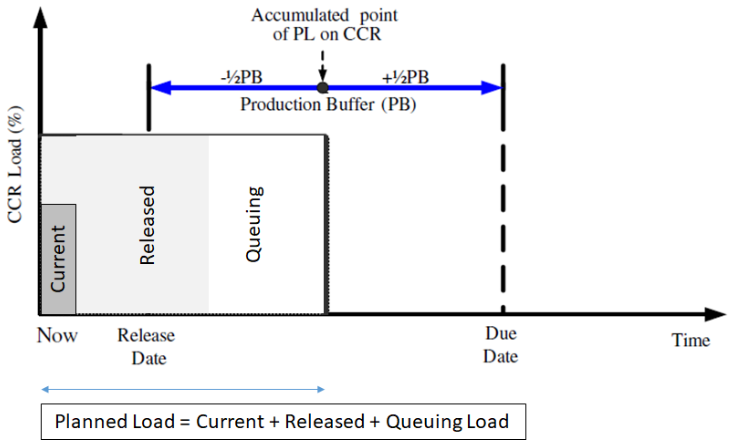

Figure 2: Planned Load (PL) at Critical Capacity Resource (CCR)

BM is a signalling tool for *execution* where there are four functions: prioritise, expedite, escalate and target (Stratton and Knight, 2010). As both the *planning* and *execution* stages are due date aligned, BM is represented in time unit, divided into three equal zones: green, yellow, and red. The buffer status (BS) of each work order is referenced against the three zones, with red zone having the highest urgency. BS is the ratio between available time and PB. An illustration of BM is shown in *Figure 3* and detailed calculations for LM and BM can be found in Lee et al. (2010) and Yeong (2019).

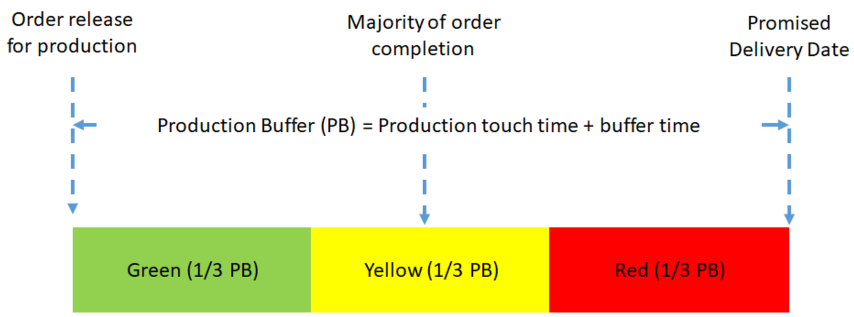

Figure 3: Illustration of Buffer Management

In Company A, the potential CCR is identified as the moulding machines, positioned at the front-end of the production route. The total load on moulding machines are monitored using PL. As the industrial accepted lead time is three weeks, a red line is drawn on PL to represent 15 working days, as shown in *Figure 4* where the red line allows management to proactively intervene. In Company A, visualisation of total load allows management to strategically deploy additional resource capacity, at the appropriate time and with adequate quantity. This has successfully exposed hidden resource capacity, evident from Company A not needing to deploy additional shifts during the peak season for the first time. To further assist *planning*, a simulation tool is developed to allow the user to visualise the impact of varying resource capacity on the CCR and buffer status of work orders. For example, instead of deploying a full shift, management can simulate and observe the resource capacity necessary for the system to return to the three-week *safety zone*.

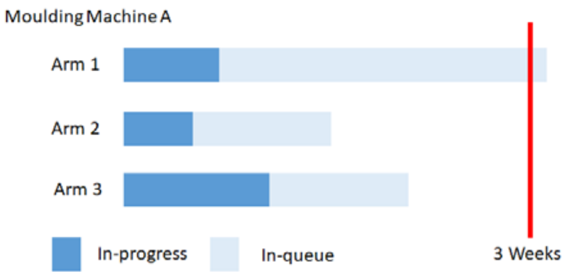

Figure 4: Plan Load and the use of Red Line in Company A

In addition to resource planning, together with BM, new work orders can be planned according to the system status. During the customer enquiry stage, there are three scenarios about the order due date: (i) willing to accept any due date proposed, (ii) has a negotiable due date, or (iii) has a fixed due date. A feasible due date is determined to facilitate the decision to accept, renegotiate, or reject an order. This is calculated by adding PB of this work order to the earliest available date of a moulding machine resource. If the due date falls later than the fixed due date, the order is rejected. If it falls in yellow or green zones of BM, the order is accepted. If it falls in the red zone, the order will be renegotiated. A customer query module is built to offer two simulated scenarios. The first is by adding the new order to the end of the total load; and the second is by considering it as an accepted order and analyse how it affects the buffer status of other orders. The simulation result will also highlight the constraint which causes an order to fall outside of the industrial accepted lead time. This allows management to make informed decisions and take an appropriate intervention in the *planning* stage.

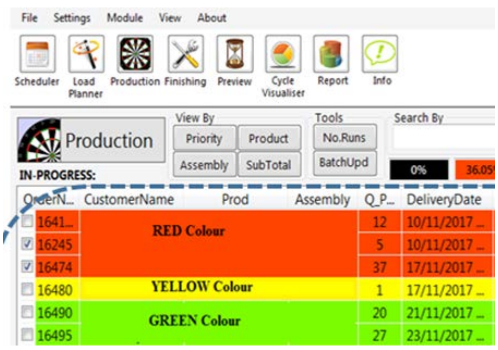

Figure 5: Work Orders with Buffer Status to facilitate execution

In the *execution* stage, as shown in *Figure 5*, the buffer status of all accepted work orders is calculated and made visual to all relevant personnel. Given that the contextual environment has various uncertainties, shop floor personnel are empowered to utilise tacit knowledge to response to the buffer status of the orders. The *prioritise* and *expedite* functions of BM avoids cherry-picking behaviour on shop floor. It also empowers shop floor personnel to utilise tacit knowledge to intervene appropriately. Where the BM signals growing instability, this needs to be *escalated* to higher management for more extreme intervention. The final function of BM utilises a record of reasons for red zone penetration that can be *targeted* continuous improvement.

Calculation of the buffer status and repopulation of the plan load are triggered by a combination of events and time. Periodically, they are regenerated daily manually refreshed by users allowing the PPC system to react in real-time.

Although the above discussion addresses the issue of when and which work order to process it did not address the relatively complex routing issues in Company A. In Company A, there is no dedicated production line with all resources shared. For example, the CCR is the moulding machines and there are multiple machines with multiple arms on which here are multiple positions to mount the moulds (as shown in *Figure 6*). The increased number of moulds on each arm will increase the production throughput. However, increasing the number of moulds will increase the setup time. The more crowded the moulds, the more time consuming it is for setup, as it normally involves the use of overhead cranes. Production throughput (capacity) of moulding machine is a trade-off between number of moulds mounted and setup time required. This is further complicated by factors such as moulding materials, mould size, mould opening design, mount frame, type of plastic resin, machine familiarity of personnel, physical condition of personnel, ambient temperature, etc. The existence of multiple machine resources with similar capacity also poses parallel machine related issues.

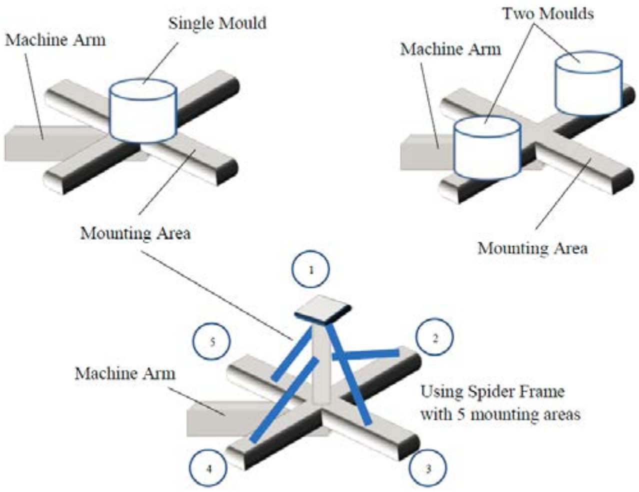

Figure 6: Illustration of physical requirements on machine arms

With the purpose of developing a practical resource allocation system, a combination of knowledge base and search algorithm are used. The knowledge base is developed based on the observation of practice and verbalised knowledge by experts on shop floor. This knowledge includes the thinking process regarding machine resource allocation and shop floor best practices through trial and error over the years and passed down by seniors. Most of the information is not crisp, with the conversation normally ending with "*it depends*".

Through further analysis, the collected data and thinking process are firstly developed into attributes and test cases. To address fuzziness, a *wildcard* test case is used, where a *wildcard mould* is assigned onto a *wildcard machine resource*. A new order will firstly be *filtered* through the test cases. The purpose of the filtering is to mimic the existing thinking process and to reduce the number of searches to be conducted in the subsequent step. A search algorithm has been developed to test the production buffer on each possible route to determine the one with the earliest deliver date, DD_E. To minimise the search time, each resource group will nominate a best *candidate* (for example, earliest availability date or *preferred* machine position). This is followed by determining the buffer status of the work order before placing it into the queueing pool, which will be subjected to the S-DBR algorithm.

To address the issue of fuzziness in data and thinking process, shop floor personnel, the human experts, are the ones who makes the final decision on machine resource allocation. Personnel can use the PPC system developed to simulate other combination before physically assign a work order onto a machine resource. To facilitate intervention, a more detailed view of plan load is developed, as shown in *Figure 7*. Each work order is colour coded according to its buffer status, allowing personnel to make decision to over-right system proposed allocation.

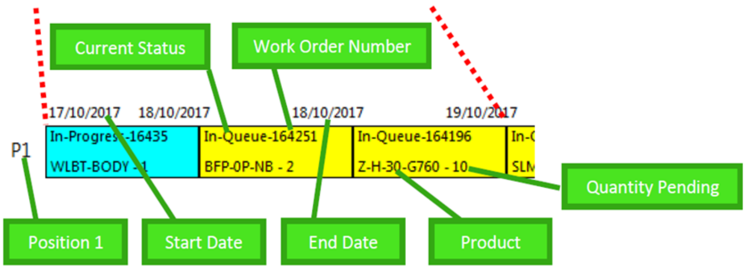

Figure 7: Detailed plan load view

Three years after implementation, the system successfully it has more than doubled its production throughput and through its integration with the Sage system, it has successfully become an integral part of the business process. This reactive PPC has been developed into a Decision Support System (DSS) with the integration of knowledge-based search algorithm and S-DBR algorithm. Detailed account can be found in Yeong (2019).

Case Study: Phase 2

Moving forward, in addition to the knowledge learnt from human experts in phase one, phase 2 intends to acquire knowledge by learning through data collected. This will be discussed by adopting the eleven activity areas reviewed in the earlier section. The eleven activity areas are further grouped into five categories to explore applicability of machine learning in the PPC of company A.

(i) Data acquisition, exploration, cleaning and formatting

Resource allocation data (such as moulding machine resource vs mould) can potentially be explored through inferential statistics for initial insights. Decision support systems could potentially be further explored to provide business intelligence by exploring market related data, such as product type.

(ii) Feature selection, extraction and transformation

From the machine vs mould and product data acquired from (i), further analysis such as statistical techniques or expert insights can be adopted to identify potential features to develop machine learning model.

(iii) Hyperparameter tuning and architecture design, model training, validation, testing and assessment.

Based on the findings in (i) and (ii), a machine learning model architecture will be developed, trained, validated and assessed. As the system has been successfully run for three years, data from year 1 and 2 can potentially be used as test cases and validated using year 3 data. Search algorithms used in the resource allocation could potentially be improved by developing new model.

(iv) Model Comparison and Selection

The activity area (iii) could potentially be repeated using different models to compare performance. In real time, multiple machine resource allocation model could potentially be used to triangulate a best proposal.

(v) Contextualised analysis and model update

Based on the existing successful platform, in addition to simulation-based activity in (iv), there is potential of conducting prototype testing in company A. The insights discovered through (i), (ii) and (iii) could potentially refine the existing algorithm used in resource allocation.

Conclusion

Noticing the theory-practice gap in PPC, researchers are driven to adopt a *reactive* approach to address the issue of uncertainties. Based on the recent review by Cadavid et al. (2020), the practicality of machine learning based PPC is still in the development stage. Of the forty papers reviewed since 2010, the simulation skewed research offers potential research area for empirical and case studies. As the industry trends towards adopting AI, the applicability of AI in PPC for SMEs warrant further research to avoid SMEs falling into the trap of merely jumping onto the bandwagon. The case study presented in this paper offers an insight into how knowledge-based AI could potentially be integrated with management philosophy based S-DBR. The synergy between both: business analytics, could potentially offer higher value to SMEs where the whole is greater than the sum of its parts.

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