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ARTICLE

Optimized material management in construction using multi-layer perceptron

Farzaneh Golkhoo and Osama Moselhi

Abstract: Construction material represents a major component of the project cost. Therefore, it is essential to control material on construction job sites. Efficient material management system requires trade-offs and optimized balance among elements of material cost including purchase cost, storage cost, opportunity cost, ordering cost, and unavailability cost. Thus, there is a need to develop an automated method for optimizing the delivery and inventory of construction materials not only in the planning phase but also in the construction phase to account for introduced changes. In this research a novel genetic algorithm – multi-layer perceptron (GA-MLP) method is proposed to generate optimized material delivery schedule. Multi-layer perceptron (MLP) is utilized to improve genetic algorithm (GA) by generating memory to overcome local minima encountered in applying GA for optimization. This automated method supports contractors to buy construction materials with the least cost and without leading to material shortage or surplus. The proposed automated method has been validated through a numerical example. The obtained results demonstrate that GA-MLP outperform GA in optimizing construction material inventory.

Key words: construction materials, construction materials management, material delivery schedule, optimization, genetic algorithm, multi-layer perceptron.

Résumé : Les matériaux de construction représentent une composante importante du coût d'un projet. Par conséquent, il est essentiel de contrôler les matériaux sur les chantiers de construction. Un système de gestion des matériaux efficace implique des compromis et exige un équilibre optimisé entre les éléments du coût des matériaux, y compris le coût d'achat, le coût d'entreposage, le coût de substitution, le coût de commande et le coût d'indisponibilité. Il est donc nécessaire de mettre au point une méthode automatisée d'optimisation de la livraison et de l'inventaire des matériaux de construction, non seulement pendant la phase de planification, mais aussi pendant la phase de construction, afin tenir compte des changements en cours de projet. Dans cette recherche, une nouvelle méthode utilisant un algorithme génétique et perceptron multicouche (AG-PMC) est proposée afin de générer un calendrier de livraison des matériaux optimisé. Un perceptron multicouche (PMC) est utilisé pour améliorer l'algorithme génétique (AG) en générant de la mémoire pour surmonter les minima locaux qui surviennent dans l'application de l'AG pour l'optimisation. Cette méthode automatisée aide les entrepreneurs à acheter des matériaux de construction au moindre coût et sans entraîner de pénurie ni de surplus de matériaux. La méthode automatisée proposée a été validée au moyen d'un exemple numérique. Les résultats obtenus démontrent que l'AG-PMC surpasse l'AG dans l'optimisation de l'inventaire des matériaux de construction. [Traduit par la Rédaction]

Mots-clés : matériaux de construction, gestion des matériaux de construction, calendrier de livraison des matériaux, optimisation, algorithme génétique, perceptron multicouche.

Introduction

Material cost can constitute 50%–60% of industrial construction project costs (Stukhart 1995; Caldas et al. 2015) and it can control 80% of the project schedule from procuring the initial materials to the delivery of the last item (Stukhart 1995; Caldas et al. 2015). Despite the significant role of material management in minimizing project cost and maximizing profit, most contractors experience problems caused by poor material management processes and encounter various issues including inaccurate warehouse records, over ordering and large surpluses of material at project completion, poor site storage practices, material shortages, late deliveries, out-of-specification material, and out of sequence deliveries, which all result in cash flow problems, low productivity, delays and cost overruns.

In another study by Rahman et al. (2013), it was shown that "late or irregular delivery or wrong types of material delivered during construction affect the utilization of other resources like manpower and equipment. Interruption to the work schedule, rework arising from wrong or out-of-order materials, double handling because of inadequate materials, material deterioration during extended storage periods, expenses associated with crews lacking proper materials, and lost items on or off site are common problems with materials in the small and medium sized construction projects (Barry et al. 2014).

Total material cost includes major categories of cost such as purchasing cost, storage cost, ordering cost, unavailability cost, and opportunity cost which is the locked up capital in material inventories. Therefore, to procure material with a reasonable cost, there should be a trade-off among these cost categories.

It is stated that small orders, frequent deliveries, and reduced inventories such as just-in-time (JIT) strategy are generally accepted rules of material management in the operational phase, but in practice, larger orders are more profitable due to full load

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transportation or discounts on the prices of materials (Sobotka 2000; Shmanske 2003). So, there are some circumstances including supply chain uncertainty, variation and uncertainty in the production process, unavailability of materials on local market, high inflation rates, discount on prices of large amounts of materials, and price cuts in case of early purchasing, which can make JIT less advantageous.

To manage and control materials on the construction sites not only a balance among cost categories has to be achieved, but also the dynamic nature of construction projects has to be taken into account. It can be concluded that without proper methods and procedures, making material purchase orders by contractors or material professionals to procure the right quantity of materials with the right quality and the least cost without delay is impossible. Hence there is a critical need to develop an automated efficient inventory control and management method to support contractors in making decisions and taking actions on how much and when to order materials that result in inventory at an optimum level with the least costs. Even though various studies have improved the material management process utilizing different methods and technologies, the researchers have optimized the total cost of inventory either at the planning phase of projects without considering the changes occurred in the construction phase or by using genetic algorithm (GA) as the optimization engine without obviating the lack of enough diversification in the generated populations, which is the limitation of GA.

This paper presents a newly developed automated method to optimize material delivery schedule based on material requirements planning (MRP) and the least total material cost. The developed method utilized GA and multi-layer perceptron (MLP). The proposed novel method follows up the progress as reflected in the last up-to-date schedule to update MRP and delivery schedules repetitively throughout the construction phase.

Background

Delving into currently available literature in the field of construction materials management resulted in dividing related researches into two domains "construction materials management", and "automated construction materials management". Automated construction materials management domain not only consists of the application of automated data collection (ADC) technologies in materials management but also computer-based materials management systems.

It can be expressed that research developments related to the first domain "construction material management" have been expanded to the following areas: (1) Site layout planning for material storage or optimization of material procurement and storage on site (Thomas et al. 2005; Jang et al. 2007; Georgy and Basily 2008; Said and El-Rayes 2011, 2012; Alanjari et al. 2014); (2) Effectiveness and performance measurement of materials management process (Plemmons and Bell 1995; Al-Khalil et al. 2004; Wickramatillake et al. 2007); (3) Efficient materials management practices and their applied approaches, materials management problems and its influences on project productivity, cost and schedule (Formoso and Revelo 1999; Kini 1999; Thomas and Sanvido 2000; Perdomo and Thabet 2002); (4) Lean construction or investigating the implementation of just-in-time (JIT) strategies in construction projects (Pheng and Hui 1999; Polat et al. 2007; Sacks et al. 2009); and (5) Material waste management and quantification (Poon et al. 2001, 2004; Jalali 2007).

Researchers came to the conclusion that managing materials on-site through paper documents were not practical in complex and large-scale construction projects, and when materials management processes were executed in a consistent manner, it was operated more efficiently. As a result, they tried to improve materials management through computerized systems and obtain more benefits such as uniformity of documents generation, efficiency, and automatic process implementation from inputting information to report generation in a matter of hours. But a computerized system alone could not ensure the accuracy of the reports upon which corrective actions or various decisions were made. In fact, the output information and reports were only as good as the input data creating them. Consequently, they applied automated data collection (ADC) technologies instead of manual data collection to reduce slow, inaccurate, and excessive amounts of collected data stored on paper to solve the issue. It can be noted that the main applications of ADC technologies in the existing studies are collecting material localization and tracking data at the construction sites, and identifying unique materials received at the job site (Golkhoo and Moselhi 2017). It should be mentioned that the focus of this section is on the studies done in the first area of the first domain.

Thomas et al. (1999) studied three types of structural steel erection project in which the delivery methods of material (structural steel members) as a component of material management were different. By quantification of labor productivity using multiple regression technique, the best delivery method of material (steel erection directly from the truck against two others including steel off-loading, sorting, and then erecting, and three bulk steel deliveries) was indicated. Jang et al. (2007) optimized the floor-level construction material layout required for multiple-floor buildings in urban areas using GA and through minimizing excessive repositioning of construction materials. This optimized floor-level construction material layout determines how efficiently to position the construction materials to minimize the travel distance between work spots and construction materials. By implementing the proposed approach in a real case, it was found that inefficiencies in positioning of construction materials at the floor-level could result in 14% increase in the construction labor material handling distance. Polat et al. (2007) proposed a simulation-based decision support system to achieve an economical rebar management system. They defined three differences between the just-in-time (JIT) and just-in-case (JIC) materials management systems including buffer size, scheduling strategy; and lot size. Then considering buffer size in terms of large, medium, and small; scheduling strategy in terms of optimistic, neutral, and pessimistic; and lot size in terms of large and small, contractors were faced with 18 alternative rebar management systems between the JIT and JIC management systems. So, through applying discrete event simulation (DES), the most economical rebar management system with the least cost of inventory at the planning stages of a project was selected. It was found that JIC was the most economical rebar management system in their case study with 4.8% savings of total cost of inventory over JIT. Georgy and Basily (2008) used GA to develop a systematic procedure for optimizing the delivery and inventory of materials. They concluded that GA is a proper optimization engine for this purpose, because the solution space for the optimization of delivery and inventory of materials is almost infinite, no specific number of orders is known in advance, material requisition schedule can be represented in a string form consisting of material quantities delivered at specific times, and resembles the chromosomes used in GA as input, and finally a near optimum solution minimizing material cost is obtained and is acceptable for all practical purposes. They applied pure GA to solve the problem without obtaining enough diversification in the generated populations to escape from getting stuck to local minima. Moreover, material unavailability cost is not considered in the GA objective function to enable the proposed method to take various scenarios into consideration. Sacks et al. (2009) tried to use computer-aided visualization tools to support a set of lean construction management requirements for both planning and control. Lean construction requirements including making the process transparent to all, just-in-time delivery of materials and flexibly to respond to change were difficult to achieve in construction projects against than in manufacturing. So, they investigated application of visual tools such as building information modeling (BIM)-based visualization user interfaces to achieve a clear mental image of what was taking place and what could be expected in the near future which supported lean construction requirements. In the research done by Said and El-Rayes (2011) a construction logistics planning model was developed in which the decisions of material supply and site layout were optimized simultaneously to minimize logistics costs (ordering cost, financing cost, stock-out cost, and layout costs). The model considered interdependencies between material supply and layout decisions and was able to measure the impact of these decisions on project delays. Yu et al. (2016) came up with a BIM-based dynamic model along with GA application for planning material laydown area on construction sites and generating optimal supply scheme. An automated material inventory control and management system has been presented by Le (2017). Geographical Information System (GIS) and a "hybrid" tracking system are used in this developed system. In this developed system, identifying material needs, ordering, transporting, storing, and tracking of materials would be possible through having access to the materials real-time information. The material procurement and logistics measures were investigated in the study by Ajayi et al. (2017) to mitigate waste generated by construction activities. They concluded that in the presence of suppliers' commitment to low waste measures, low waste purchase management, effective materials delivery management and waste efficient Bill of Quantity, logistic and procurement process is waste efficient. It is expressed that commitment to a take-back scheme, procurement of waste efficient materials/technology, use of minimal packaging, use of just-in-time (JIT) delivery system, and prevention of over ordering are important for mitigating waste through material procurement processes.

In a nutshell, optimization of material procurement and storage on site through regular optimization engine, integration of the materials management processes, integration of materials localization and tracking data with the computer-based materials management systems, positioning and tracking critical resources, comparing as-planned and as-built status are the main subjects of the existing studies. The developments made by the existing researches have the potential to enhance efficiency in construction material management, but a question has not been properly answered by applying the existing methods. The question is: Which material and how much of that material must be ordered and bought on which day to result in the least cost without material shortage or surplus?

Proposed automated GA-MLP optimization algorithm

The proposed automated method is designed to generate optimized material delivery schedules as a small component of an automated construction material management system (MMS). Figure 1 illustrates the first module of the MMS entitled "preconstruction module" in which the proposed GA-MLP method has been developed to perform its first two steps. These steps include generating material requisition schedule and optimized material delivery schedule. Detailed explanation of the pre-construction module including all the steps, databases, and their interrelationships is out of the scope of the current paper. But in a holistic view, in the first step "material requisition schedule", project schedule and material specification data stored in databases are the inputs and the required quantities of each material on each day of the construction phase is the output. The output of each step is used as an input to the following step automatically. So, by knowing the required amount of each material on each day, an optimized delivery schedule for each material is generated using the developed GA-MLP method in the second step. In the next step, a schedule for buying materials is developed based on material lead time, required preprocessed time, and administrative time along with the optimized material delivery schedule from the previous step. Lead time for each material is the time between the placement of an order and the delivery of that material which can be calculated by a probabilistic approach, preprocessed time is the amount of time required in the shop to make fabricated materials ready for transportation, and administrative time demonstrates the time required to issue a purchase order (PO) to a vendor. In fact, this schedule defines the dates for issuing preliminary purchase orders for all the materials. Then according to the issue dates of preliminary purchase orders, in the next step "Purchase Order", the final purchase orders are issued on the predefined dates. Finally, in the last step, the required materials have to be delivered, received, and checked at the construction site based on the optimized material delivery schedules. All the differences between planned and actual material delivery and all other changes during construction phase are reflected in the project schedule and then are used as an input to generate "material requisition schedule" and "optimized material delivery schedule". On top of the main reports such as material requirement schedule, optimized delivery schedule, and the list of issue dates of preliminary purchase orders, the developed module can give warnings to the contractors or material professionals about the various due dates to prevent from material shortages and consequently schedule delay.

As such the developed method is expected to assist project managers to avoid early, excess, and (or) late purchasing of materials, it also assists them to procure materials with the least cost and on time. As stated earlier this paper focuses on the first two steps, which are described below.

Material requisition schedule

Required steps to develop material requisition schedule are depicted in Fig. 2. The following information is used as inputs to this process:

- Project schedule with high level of details (Activity level) which is integrated with construction elements and all the required materials are assigned to the activities on daily basis.
- Construction material data and their specifications. For instance, site pre-processed time for materials requiring assembly prior to installation at the construction site.

There are various variables in this proposed algorithm as follows:

- Project duration is shown by D (time unit is day).
- Materials have been shown by j and it is assumed that there are k materials in a project, so $j = 1, 2, \ldots, k$.
- Activities have been shown by i and it is assumed that there are n activities in a project, so $i = 1, 2, \ldots, n$.
- Since the developed algorithm has to be run on each day of the project, it needs to know the current date which shows that the project is on which day of its duration. The current date in the system is shown by T_C. It is obvious that the first day of the project schedule has a special date, but it can be shown by $T_C = 1$. So, $T_C = 1, 2, \ldots, D$.
- Early start and early finish dates of all the activities are used in this system to avoid uncertainties and they are shown by ES_i and EF_i for activity i, respectively.
- The preprocessed time for the materials requiring assembly prior to installation at the construction site is shown by T_{sp}. It can be obtained from the construction material specifications input data.
- The required amount of material j assigned to each activity i on specific days is shown by q_{ij}.

As shown in Fig. 2, having input data, the algorithm selects a special material and consider it as $j = 1$, then it starts to calculate the total required amount of material $j = 1$ on each day of the project. So the first day of the project is selected ($T_C = 1$), and the

Fig. 1. Pre-construction module.

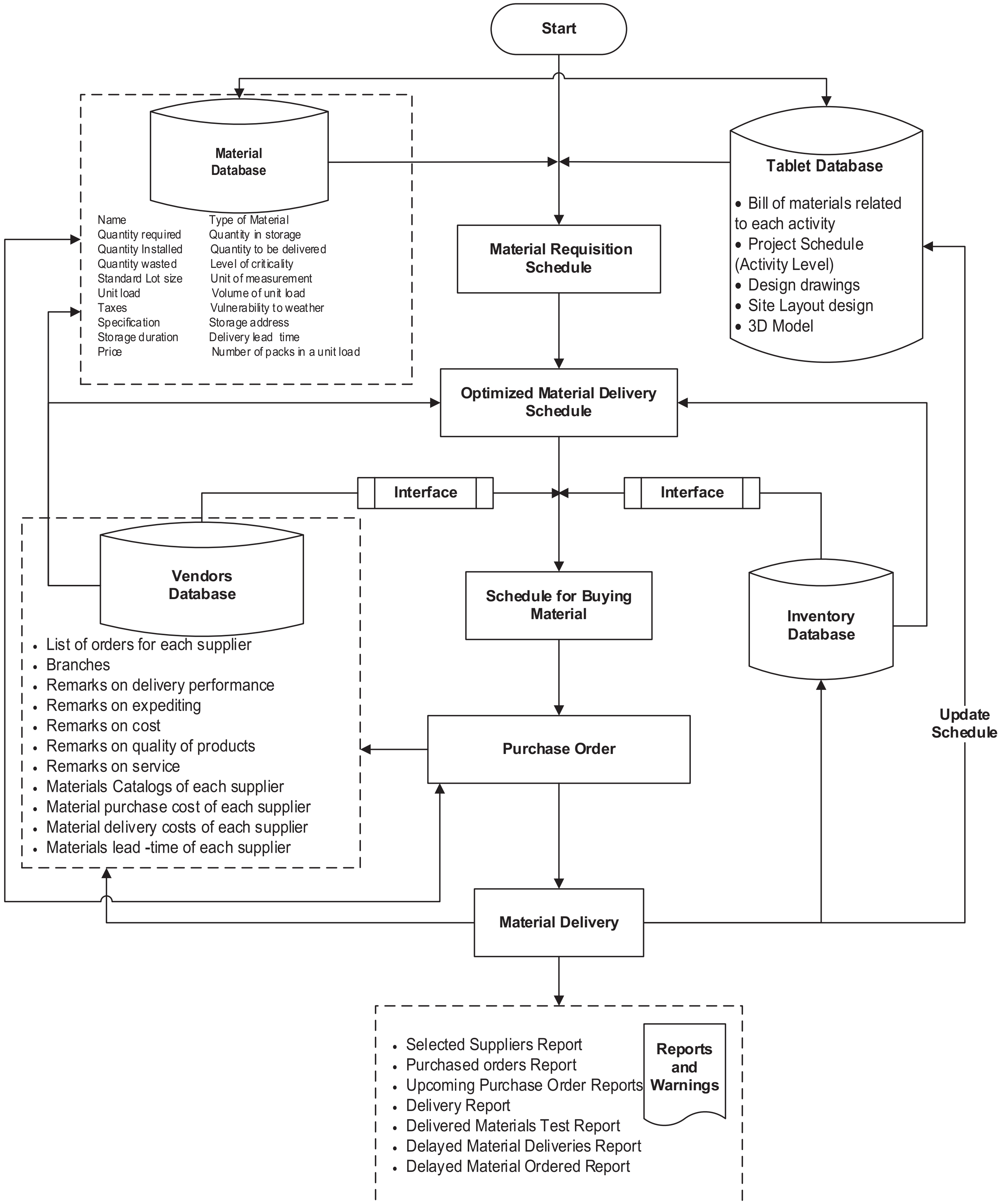
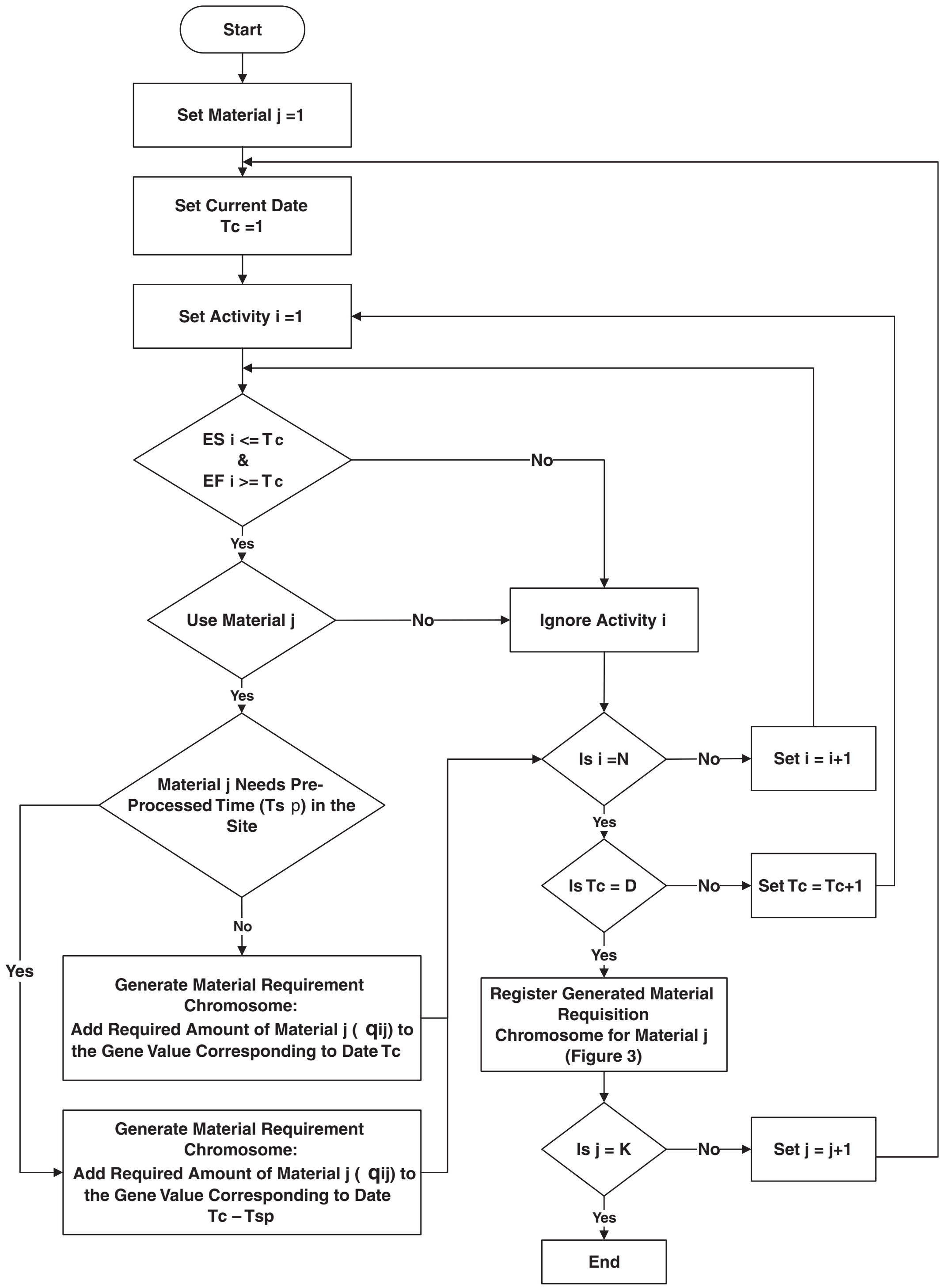


Fig. 2. Algorithm for generating material requisition schedule.



system compares the Early Start and Early Finish dates of all the activities (from $i = 1$ to $i = n$) with $T_C = 1$ ($ES_i \le T_C$ and $EF_i \ge T_C$), to identify the ongoing activities which use material $j = 1$ on the first day.

Afterwards the required amount of material $j = 1$ relevant to the identified activities (q_{ij}) are found and summed up ($\sum_{i=1}^{n} q_{ij}$). The calculated value $\sum_{i=1}^{n} q_{ij}$ must be assigned to $T_C = 1$, but if material $j = 1$ needs pre-processed (T_{sp}) time at the site, the calculated value $\sum_{i=1}^{n} q_{ij}$ has to be assigned to $T_C - T_{sp}$. It indicates that the material $j = 1$ is required on the day $T_C - T_{sp}$ with the amount of $\sum_{i=1}^{n} q_{ij}$.

All these steps are repeated for material $j = 1$ from the first day of the project ($T_C = 1$) to the last day ($T_C = D$). The output of this process can be represented in the form of a vector with D columns for material $j = 1$ as shown in Fig. 3. The columns demonstrate the days of the project duration and the nonzero elements of this vector indicate the required amount of material $j = 1$ on those special days. All the mentioned processes would be implemented for all the materials from $j = 1$ to $j = k$. Finally, there would be k vectors for k materials.

Fig. 3. Material requirement vector for material *j*.

$T_C = 1$	$T_C = 2$	$T_C = 3$	….				$T_C = D-2$	$T_C = D-1$	$T_C = D$
$q_{T_C} = \sum_{i=1}^{n} q_{ij}$	$q_{T_C} = \sum_{i=1}^{n} q_{ij}$	$q_{T_C} = \sum_{i=1}^{n} q_{ij}$	…	…	…	…	$q_{T_C} = \sum_{i=1}^{n} q_{ij}$	$q_{T_C} = \sum_{i=1}^{n} q_{ij}$	$q_{T_C} = \sum_{i=1}^{n} q_{ij}$

Fig. 4. Material delivery chromosome for material *j*.

$T_C = 1$	$T_C = 2$	$T_C = 3$		….			$T_C = D-2$	$T_C = D-1$	$T_C = D$
Q_1	…	Q_3	…	…	…	…	Q_{D-2}	Q_{D-1}	Q_D

Optimized material delivery schedule

Scheduling deliveries of materials not only can prevent material shortages but also can minimize warehousing as much as possible. So, to procure required materials with the least cost and avoid from early, late, excess, and insufficient purchasing, a novel automated method to generate optimized delivery schedule for each material is developed.

In fact this step answers the question of having the required amounts and dates of each material, how these materials can be bought and delivered resulting in the least cost considering minimum order quantity (minimum shipping), and storage space. To answer the mentioned question and generate optimized delivery schedule for each material a novel integrated GA-MLP technique is proposed and explained in detail in the following subsections:

Genetic algorithm optimization

Genetic algorithms (GAs) as the simulations of natural selection are the earliest, most famous, and most widely-used evolutionary algorithms (EAs) (Simon 2013). A great diversity of constrained and unconstrained optimization problems can be solved applying GA as a universal method (Holland 1975). In fact, genetic algorithm as a type of optimization engine tries to find the optimal solution(s) of a computational problem in terms of maximizing or minimizing a particular function. Fitness functions for optimization, initial population of chromosomes, and rules to create next generations are the GA components. The initial population is a group of possible solutions of the given problem. GA will modify the initial population in consecutive iterations to obtain a better solution.

As Carr (2014) stated, the way of translating candidate solutions into chromosomes and defining fitness function are the main elements affecting the performance of a genetic algorithm. Other factors such as the probability of crossover, the probability of mutation, the size of the population, and the number of iterations can be modified regarding the algorithm's performance through a few trial runs. So to perform encoding of each candidate solution of buying a special construction material during the construction phase into chromosomes, chromosomes are employed to indicate the various possible amount of material $j = 1$ which can be bought on different days of project duration from $T_C = 1$ to $T_C = D$ as shown in Fig. 4. The number of genes represents the total number of time units of project duration, and gene values indicate the amount of material that has to be ordered and bought at that particular time.

The objective function of GA algorithm is minimizing the total material cost. So, it is required to calculate the total cost of material *j* which would be delivered based on each material delivery chromosome. Each chromosome that leads to the lower cost can be selected as the better solution. If the terminating condition is not met, the obtained better solutions will be recombined using genetic operators to breed new better solutions among generations. To calculate total material cost using objective function, the two following scenarios have been taken in to consideration:

First scenario: shortage of material is prohibited

In fact in this scenario, encounter with material shortage is not acceptable even if the cost of buying and storing materials in advance results in a higher total material cost comparing the total material cost including material unavailability cost. So, in this scenario the objective function is considered as eq. 1. According to the study done by Georgy and Basily (2008), total material cost include four major cost categories, purchase cost of a material which is the unit purchase price from a vendor including transportation and freight expenses, order cost which demonstrates the administrative expense related to issuing a purchase order (PO) to a vendor, opportunity costs which are the losses resulted from tied-up funds in the inventory and cannot be invested for other beneficial purposes and finally storage cost which is the cost related to the warehousing, handling, store workers, and equipment inside the warehouse. So, through the following equations, the total material cost can be calculated by considering the time value of money:

$$\text{(1)}\quad \begin{aligned}\text{Minimize Total Material Cost} &= \text{Minimize (Purchasing Cost} + \text{Ordering Cost}\\ &\quad + \text{Opportunity Cost} + \text{Storage Cost)}\end{aligned}$$

$$\text{(2)}\quad \text{Purchasing Cost} = \sum_{N=1}^{N_p}\sum_{d=1}^{L_N}(Q_d \times P_d)(1+i)^{N-1}$$

$$\text{(3)}\quad \text{Ordering Cost} = \sum_{N=1}^{N_p}(L_N \times C_O)(1+i)^{N-1}$$

$$\text{(4)}\quad \text{Opportunity Cost} = \sum_{N=1}^{N_p}\sum_{T_C=365(N-1)+1}^{365N}(SQ_{T_C} \times I \times P_{\text{average}})(1+i)^{N-1}$$

$$\text{(5)}\quad P_{\text{average}} = \text{Purchasing Cost}\Big/\sum_{N=1}^{N_p}\sum_{d=1}^{L_N}Q_d$$

$$\text{(6)}\quad \text{Storage Cost} = \sum_{N=1}^{N_p}\sum_{T_C=365(N-1)+1}^{365N}(SQ_{T_C} \times C_s)(1+i)^{N-1}$$

where

N_p is the total project duration in terms of year;
L_N is the number of material orders/deliveries made in year N;
Q_d is the quantity of material for order d;
P_d is the unit price of material for order d;
P_{average} is the average unit price of material;
C_O is the average administrative cost for making a single order;
SQ_{T_C} is the stock quantity at time T_C;

C_s is the storage cost for an individual unit quantity per unit time;
I is the interest rate per unit time;
i is the annual escalation rate;

Some input data such as purchase cost and delivery cost of materials related to various vendors are available in databases of the whole developed system. Since each vendor has its own price and discounts for bulk purchases, there is a need to select proper potential vendors to be able to calculate the total material cost for each generated chromosome in the objective function. The associated process of the potential vendors' selection for the materials is developed as well in the MMS, but its elaboration is out of the scope of this paper. So, it is assumed that the required input data are available to be used to calculate the total material cost.

Computing the amount of stock quantity at time $T_C(SQ_{T_C})$ is a prerequisite of storage cost and capital cost calculation for each generated material delivery chromosome at time T_C. Therefore the eq. 7 is used to calculate SQ_{T_C}:

$$(7)\qquad \text{Stock quantity at time } T_C(SQ_{T_C}) = SQ_{T_C-1} + Q_{T_C} - q_{T_C}$$

where

SQ_{T_C-1} is stock quantity at time $T_C - 1$,

Q_{T_C} is the material quantities which have to be ordered at time T_C which equals to Q_d when order d is taken place at time T_C,

q_{T_C} is the required material quantities at time T_C (These values can be obtained from the material requirement vector for each material; Fig. 3).

Second scenario: shortage of material is not prohibited

Contrary to the first scenario, in this scenario, material shortage can be acceptable at different time points of construction phase if the total material cost including the cost of material unavailability is less than the total material cost without material shortage. So, in this scenario the objective function is considered as eq. 8.

$$\begin{aligned}(8)\qquad &\text{Minimize Total Material Cost}\\ &= \text{Minimize (Purchasing Cost} + \text{Ordering Cost}\\ &+ \text{Opportunity Cost} + \text{Storage Cost} + \text{Unavailability Cost)}\end{aligned}$$

As Said and El-Rayes (2011) have stated, to calculate material unavailability cost, first step is to estimate material-related project delay. The algorithm to calculate project delay due to material shortage is presented in Fig. 5. In fact, when there is a delayed delivery of a special material at a special time point of construction phase, two factors have to be defined to calculate the project delay. First factor is identifying the ongoing activities at that special time point consuming that specific material with their total floats. The second factor is defining the activities among them which cannot be completed due to material shortage after assigning the ordered quantity of that specific material to the activities with minimum total float. Since the delay of each activity and consequently the project delay is calculated based on the material consumption rate, so after identifying and updating the affected ongoing activities by material shortage at different time points (from $T_C = 1$ to $T_C = D$ of each chromosome as a candidate solution), the project schedule can be updated and the amount of project schedule delay (D_p in Fig. 5) can be calculated by subtracting the planned project duration from the last updated project duration. As illustrated in Fig. 5, since there is k material in a project, the mentioned process is performed for each material from $j = 1$ to $j = k$ to calculate the total material cost for chromosomes as candidate solutions of buying construction materials during the construction phase while the material shortage is allowed.

So, according to the study done by Said and El-Rayes (2011), unavailability cost is calculated according to eq. 9 considering time value of money:

$$(9)\qquad \text{Unavailability Cost} = (D_p \times C_d)(1 + i)^{N_p}$$

where

C_d is the cost resulted from project schedule delay due to material shortage. It includes project liquidated damage per day and time-depended indirect cost per day;

D_p is the project schedule overrun in terms of number of days.

It should be noted that some constraints satisfaction has to be performed during the GA optimization to check the feasibility of each generated chromosome. The following constraints are considered:

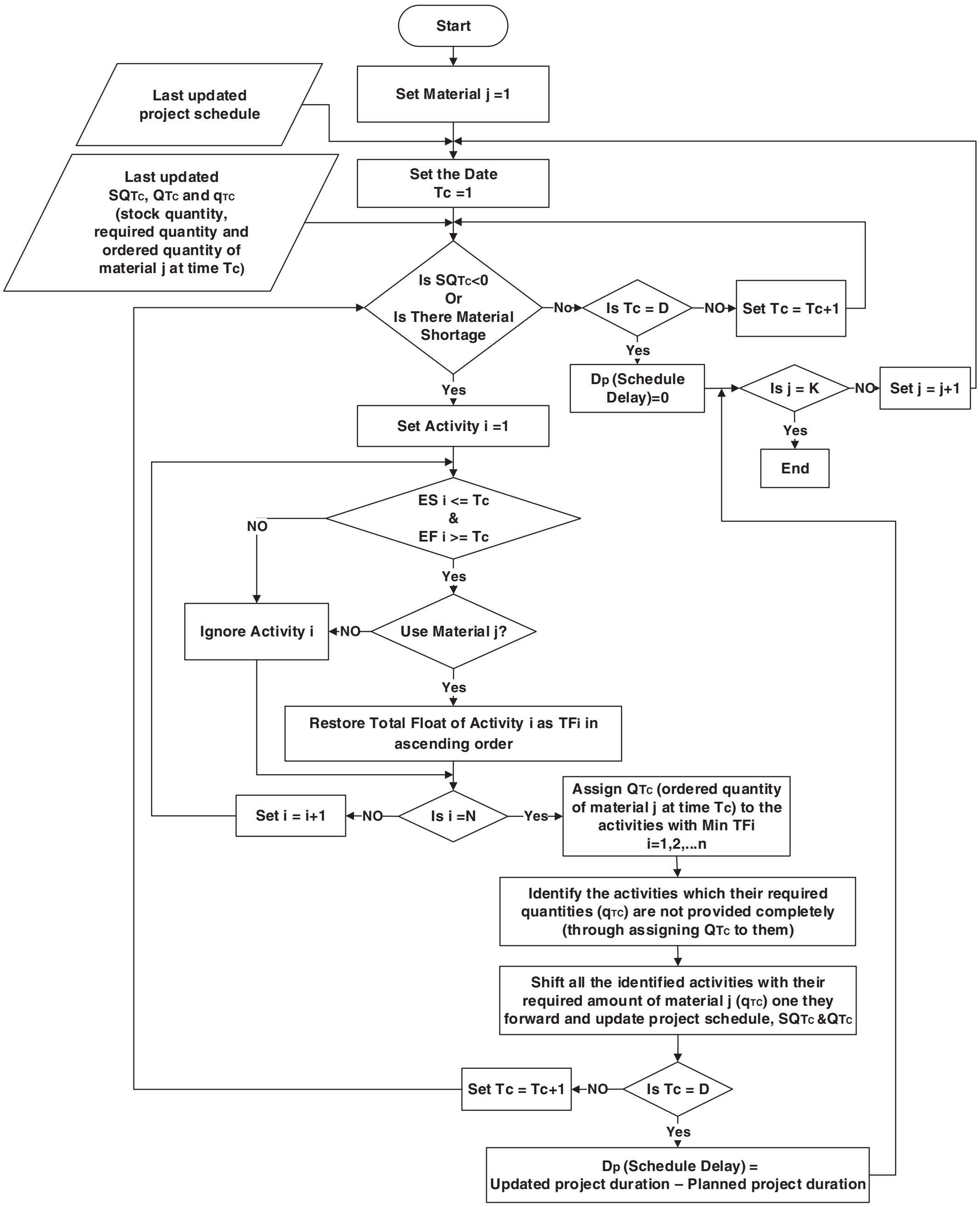
- $0 \le SQ_{T_C}$ (stock quantity at time T_C) $\le Q_{S_j}$ (max storage capacity for material j) which means there should not be any shortage of material during the construction phase and the storage space has to be considered as a limitation while ordering materials. This constraint is applied in the first scenario.
- SQ_{T_C} (stock quantity at time T_C) $\le Q_{S_j}$ (max storage capacity for material j), this constraint is applied to the second scenario because material shortage is not prohibited in the second scenario but the storage space should be considered as a limitation.
- Q_{T_C} (material quantities ordered at T_C) $\ge Q_{MS_j}$ (minimum shipping quantity for material j) in which Q_{MS_j} is an integer number showing the minimum quantity of material j which can be shipped to the construction site. This constraint is applied in both scenarios.
- The last constraint shows that at the end of the project, the total quantity of bought materials must be equal to the total quantity of required materials. In fact, there should not be surplus quantity of material at the end of the project. So, this constraint is applied for both scenarios and can be shown by $\sum_{T_C=1}^{D} Q_{T_C} - \sum_{T_C=1}^{D} q_{T_C} = 0$.

Similar to a greedy optimization algorithm, in each iteration GA selects the fittest chromosomes. In other words, without any memory, GA makes a locally-optimal choice in each generation with the hope that these choices could lead to a globally-optimal solution using various operators. So, to avoid from the major limitation of GA, which is getting stuck at local optimal values, MLP is combined with GA to create a memory of the fittest solutions previously found and improve the probability of identifying global optimal solutions. In fact, MLP as a feed-forward neural network has not been used in terms of a classifier, but it is integrated with GA only to generate memory for GA to follow the trend of data. Creating memory means that GA can memorize properties of its previous generations. Since in pure GA, after applying crossover and mutation in the current population, everything else will be removed, MLP is integrated to retain the trend of data associated with the previous generation. The next section is a brief explanation of MLP as a kind of artificial neural network (ANN).

Artificial neural network (ANN) and multi-layer perceptron (MLP)

The procedure of processing information in ANNs is similar to that of biological neural systems (Morgan et al. 1991). Neural networks are made up of many artificial neurons. Neural networks in which the neurons in each layer feed the next layer as their output until the final output is obtained are called feed-forward networks. As Shirvany et al. (2009) has stated, due to structural flexibility, good representational capabilities and availability of a large number of training algorithm of feed-forward networks, they are the most popular fully connected network architectures. MLP networks are also a kind of feed-forward neural networks in which different transfer functions can be applied based on the various conditions. MLP networks involve at least three layers entitled "input layer, hidden layer, and output layer". The archi-

Fig. 5. Algorithm for computing materials-related project delay.



tecture of the proposed MLP includes four hidden layers followed by sigmoid activation function. Hidden layers are not subjected for any up or down-sampling. Based on several experiments, densifying this simple architecture not only does not improve the performance of the final model, but also is costly in runtime and may lead to many delays in training process. Moreover, very simple architecture (i.e., with 1, 2, or three hidden layers) will not result in reliable weight vectors.

While the application of ANN is expanding in different domains, a number of ongoing researches are focusing on the selection of the ANN architecture and its efficient training procedure. These researches are trying to combine ANN and GA to enhance the performance of their proposed networks (Seiffert 2001; Nasseri et al. 2008; Divya et al. 2014; Allahkarami et al. 2017). In fact, GA is used to train and optimize the networks to increase the accuracy and efficiency of classification and prediction done by ANN. Back propagation training algorithm is frequently used in ANN to adjust the weights through comparison between the desired and actual network response and as Allahkarami et al. (2017) have stated, it may trap ANN into the local minima and lead to converging slowly. So, integrating GA with ANN can optimize the initial weights of ANN and improve its performance. In this paper, as mentioned earlier, MLP has not been applied as a classifier; it is integrated with GA only to generate memory for GA to follow the trend of data. MLP is integrated with GA in a novel algorithm to obviate the shortcoming (local minima and the lack of memory) of GA while generating the optimized material delivery schedule. Each material should be considered separately from the beginning, so after selecting a special material as material *j*, the following procedure is performed in the proposed algorithm. The developed GA-MLP algorithm is illustrated in Fig. 6 as well.

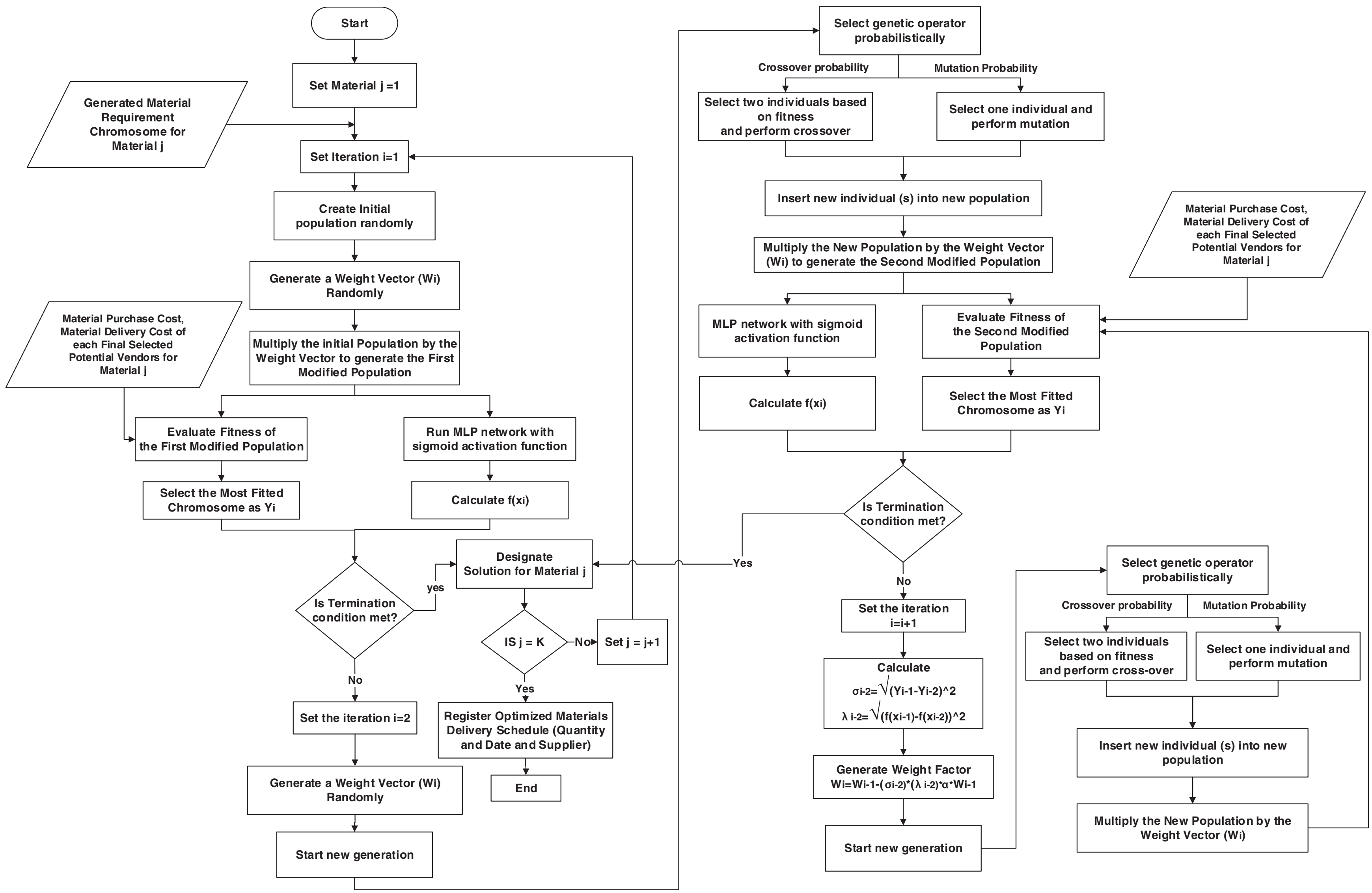


Fig. 6. GA-MLP algorithm to generate the optimized material delivery schedule.

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In the first iteration ($i = 1$) an initial population presenting different possible solutions of buying a special construction material during construction phase is generated randomly. In fact, there is no official reasoning around initializing the proper values in GA. But based on our experiment, using material requirement vector can help the performance of the proposed algorithm in terms of convergence, then MLP network is initialized with random weights (W_i) and it is fed with the initial population from GA to generate modified population (multiplying the initial population with the weight vector). In other words, MLP functionality is finding a regression between the current population and the previous generation. The reason for multiplying MLP weight vector to GA population is biasing the current chromosomes to the proper direction, since MLP weight vectors are being updated by gradient descent scheme and the better MLP training procedure is done, the better generation is expected to be produced. Sigmoid function is selected as the activation function in MLP to generate the output. Thus, on one hand the modified population (which is the output of hidden layer) is used as an input for sigmoid activation function to generate $f(x_i)$ as the output of MLP network and on the other hand modified population has to be evaluated against the objective function which is minimizing the total material cost. The most fitted chromosome (which leads to the lower cost) is selected as Y_i and if stopping criteria is not met, the next iteration is performed. In the next iteration ($i = 2$), the better individuals of the former population are selected and recombined through applying crossover and mutation operators probabilistically to breed new better solutions as a new population, generated offspring's gene values should be checked against the constraints to remove infeasible solutions. As GA passes through the second iteration, MLP will get ready to start its second epoch. Though based on the MLP concepts, epochs should be a static value to control over fitting, in the proposed algorithm, epochs is set to be equal to GA's iteration as a dynamic hyper-parameter. So second weight factor is generated by MLP randomly (W_i) and MLP is fed with the new generated population from GA to form second modified population (multiplying the new population with the second weight vector). Similar to the previous iteration, on one hand, this second modified population is used as an input for sigmoid activation function to generate $f(x_i)$ as the output of MLP network and on the other hand, modified population is evaluated against GA objective function and the most fitted chromosome is selected again as Y_i and if the population is not converged towards a single solution (stopping criteria is not met), the next iteration is performed.

After first and second iteration or epoch as illustrated in Fig. 6, the weight vectors should be updated for the next iteration with respect to a specific policy as the following:

$$W_i = W_{i-1} - (\sigma_i \times \lambda_i \times \alpha \times W_{i-1}) \tag{10}$$

where W_i is the new weight vector, W_{i-1} is the previous obtained weight vector, σ_i is called error value which is the difference between two previous most fitted chromosomes ($\sigma_i = \sqrt{(Y_{i-1} - Y_{i-2})^2}$). In fact the policy for computing the error is as computing the L2-norm between the fitted chromosomes of the current and previous generation in GA. The term λ_i is the difference between two previous MLP network outputs (sigmoid function output $\lambda_i = \sqrt{(f(x_{i-1}) - f(x_{i-2}))^2}$), and α is learning rate ($0.1 < \alpha < 0.3$). After calculating the new weight vector for each iteration, like the previous iterations, all the following steps are performed as a loop in consecutive iterations until an individual chromosome reaches certain fitness.

A new and better solution as a new population is obtained through crossover and mutation operators, and then infeasible solutions are removed from the new population by checking offspring's gene values using constraints. In the next step MLP is fed with this new generated population to form new modified population (multiplying the new population with the new weight vector). The term $f(x_i)$ is calculated using sigmoid activation function as the output of MLP network as well as Y_i as the most fitted chromosome through evaluating modified population against GA objective function. If the error value is less than its predefined threshold, then the termination condition is met and the fitted chromosome is selected as the optimized material delivery schedule. Since there is k material in a construction project, all the steps of the proposed algorithm have to be repeated for each material ($j = 1$ to k).

It is worth noting that in this study, the selected and applied methods for the genetic operators of selection, crossover and mutation are roulette-wheel, stochastic method, and random negate method respectively. Different stopping criteria could be defined including a specific number of iterations, a predetermined threshold of error value, and a predetermined threshold for the improvement value in the objective function over many consecutive generations. In this study the algorithm comes to a point of convergence when the error value is less than a specified threshold. Finally, there would be k optimized delivery schedule chromosomes for k materials in which a zero value indicates that no delivery takes place at that particular day, while nonzero values show that there are deliveries at these days, and if materials are delivered based on these schedules, the total material procurement cost will stand at the minimum level.

Proposed GA-MLP algorithm is coded in a user-friendly computational platform using MATLAB. It can be used as a stand-alone application or can be integrated with the other algorithms in MMS. The developed software is a tool for generating optimized material delivery schedule. A graphical user interfaces (GUI) in MATLAB (Figs. 7 and 8) is also developed to simplify data entry and reporting.

Numerical example to evaluate GA-MLP algorithm performance

The performance of the newly developed automated method is evaluated using a numerical example of the construction of two office buildings. In fact, the outputs of GA-MLP algorithm are compared with the outputs of the application of pure GA optimization in the same case. To simplify the comparison, first scenario in which material shortage is prohibited during the construction phase and only one material which is reinforcing steel (rebar with diameter ≥20 mm) are selected. The project schedule shows that the buildings have to be constructed in 64 weeks. It is worth noting that based on the size and complexity of the project, the developed algorithm can generate optimized material delivery schedule on daily, weekly, and (or) monthly basis. The required data to run GA and the proposed GA-MLP algorithm is shown in Table 1. By having the project schedule in which materials are assigned to the activities and by following the developed algorithm shown in Fig. 2, material requirement vector is generated and illustrated in Fig. 9 and Fig. 10. Using the input data from Table 1 and the following parameters and by applying eqs. 1 to 7, it is possible to run GA and GA-MLP algorithm to generate optimized material delivery schedule for rebar:

- Population size: 200
- Number of Generations: 200
- Number of epochs: 200
- Crossover probability: 0.85
- Mutation probability: 0.06
- Termination condition: $\alpha \leq 0.013$

The following constraints have been taken into account as well:

Fig. 7. User interface for optimized material delivery schedule (GA-MLP). [Colour online.]

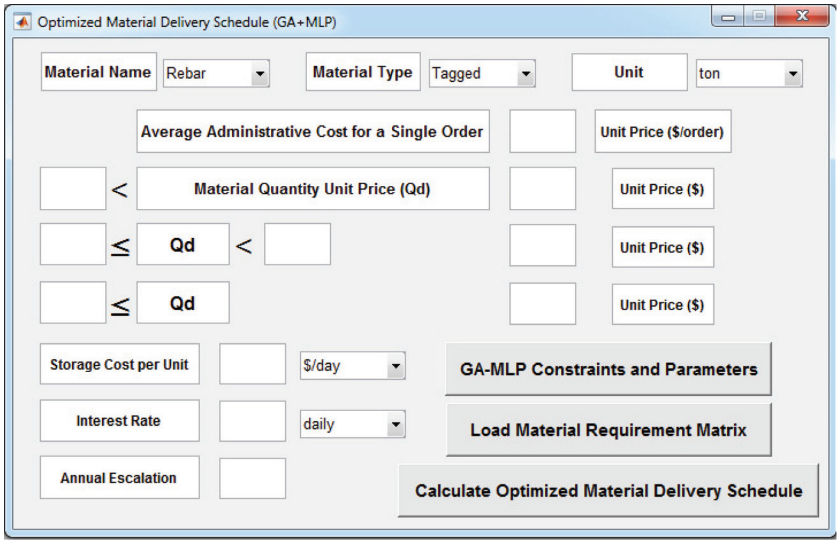


Fig. 8. User interface for GA-MLP constraints and parameters. [Colour online.]

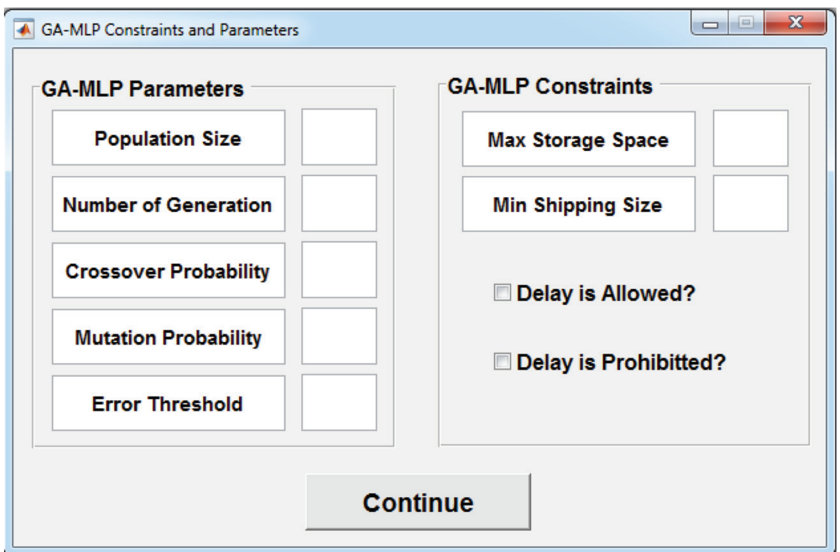


Table 1. Case study input data.

Cost type	Symbol	Amount	Unit
Average administrative cost for a single order	C_O	10	$/order
Unit price for order d	p_d	710 if $Q_d < 100$ 628 if $Q_d \geq 100$	$/ton
Storage cost for an individual unit quantity (ton)	C_s	40	$/week
Weekly interest rate	I	0.0003	NA
Annual escalation rate	i	0.015	NA

- $0 \leq SQ_{T_C}$ (stock quantity at time $T_C \leq 200$ (max storage capacity (ton)) which means there should not be any shortage of material during the construction phase
- Q_{T_C} (material quantities per order) ≥ 10 (min shipping quantity (ton)); and
- $\sum_{T_C=1}^{D} Q_{T_C} - \sum_{T_C=1}^{D} q_{T_C} = 0$, which shows that there should not be surplus quantity of material at the end of the project.

The outputs obtained from GA-MLP algorithm run are illustrated in terms of optimized rebar delivery schedule (the near optimum chromosome as the final output of the algorithm) in combination with rebar stock level during the construction phase (output of eq. 7) in Fig. 11. This figure indicates that in this project, if rebar is bought according to the red columns, it will result in the least cost, without leading to rebar shortage or surplus. It is worth noting that the numbers in the left vertical axis related to the optimized rebar delivery indicate that how much rebar on which week has to be bought if a contractor or a material professional tends to procure rebar with the least cost without any shortage during construction phase or surplus at the end of the project. In this optimal solution which results in the minimum cost, maximum storage space, and the minimum shipping size are considered as well. Right vertical axis specifies rebar quantity in the

Fig. 9. Required material (rebar with diameter ≥20 mm) during the construction phase. [Colour online.]

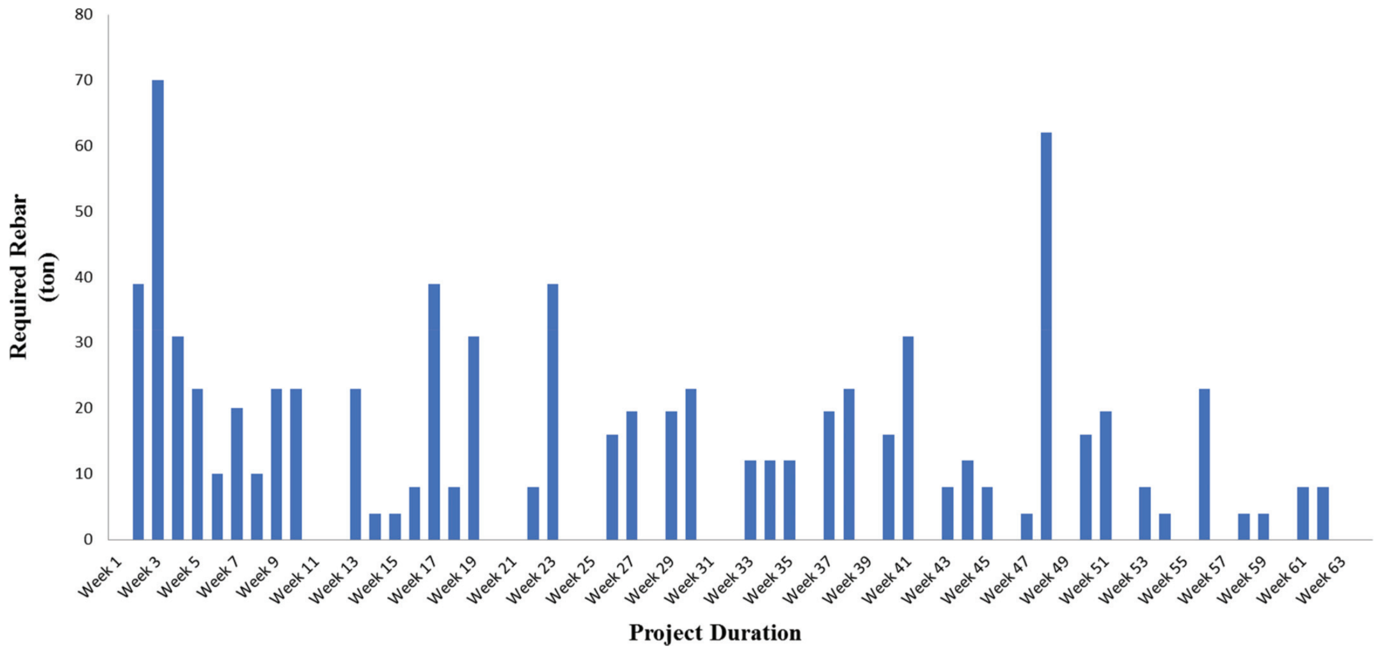


Fig. 10. Rebar requirement vector (ton/day).

W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	…	W60	W61	W62	W63	W64
Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	…	Q60	Q61	Q62	Q63	Q64
0	39	70	31	23	0	0	0	23	23	…	0	8	8	0	0

Fig. 11. Optimized rebar delivery schedule and rebar stock level (GA-MLP algorithm). [Colour online.]

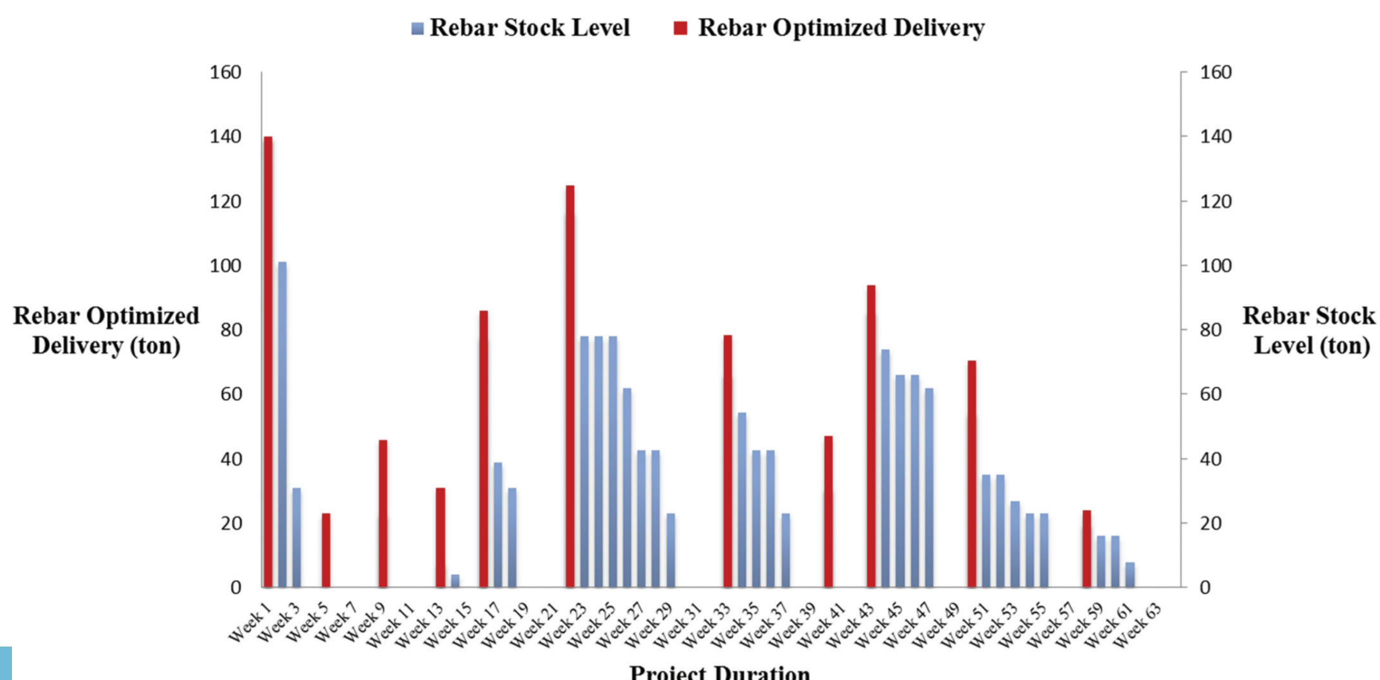


Fig. 12. Rebar delivery, consumption, and stock level (GA-MLP algorithm). [Colour online.]

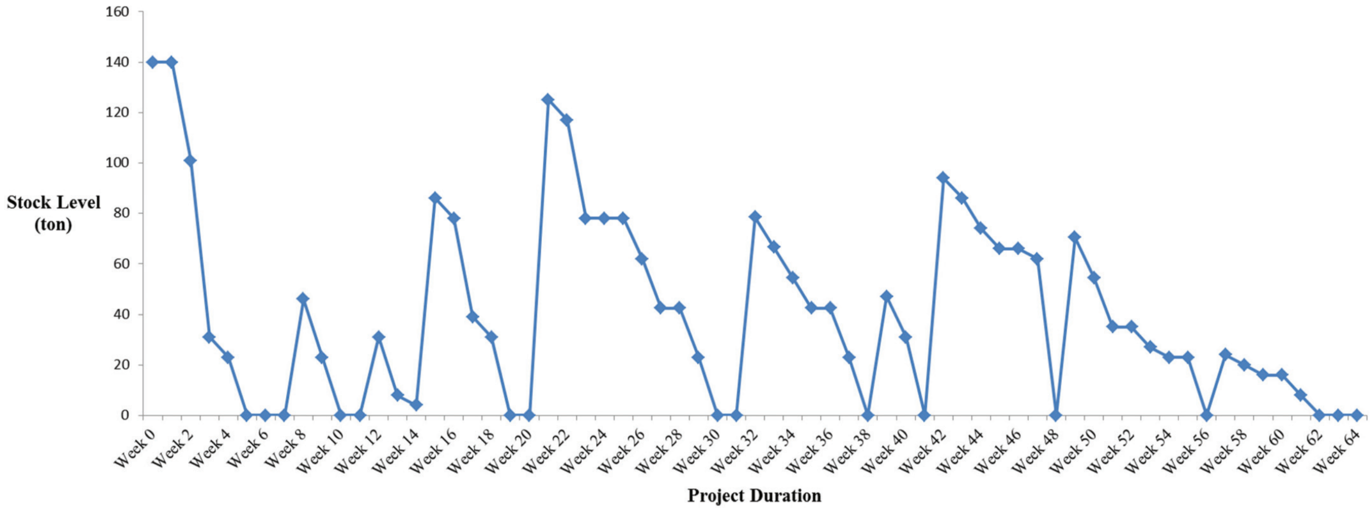


Fig. 13. Convergence of total material cost (objective function) in the 200th generation (GA-MLP algorithm). [Colour online.]

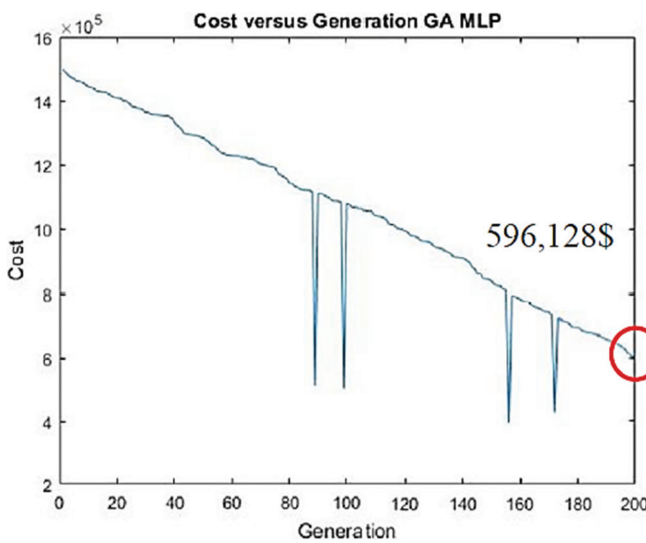
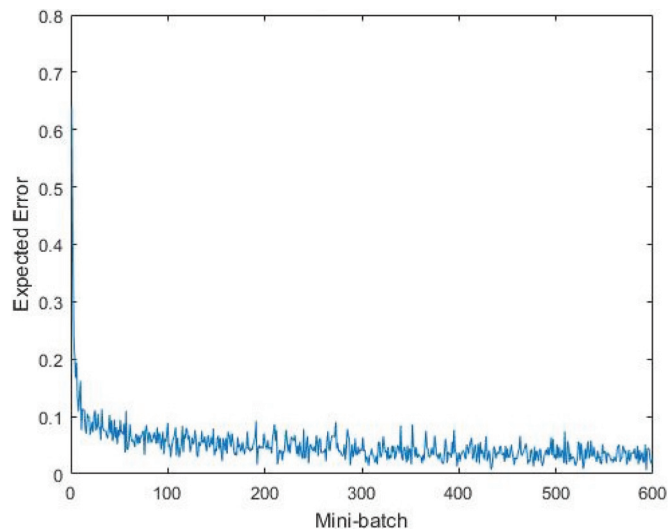


Fig. 14. Error in GA-MLP algorithm. [Colour online.]



storage in each week. Figure 12 illustrates the optimized rebar delivery schedule in one scenario including rebar delivery, consumption and stock level. For example, it is shown that a batch of 140 tons of rebar is delivered in the first week, but there is no rebar consumption during this week. So, the rebar stock level remains constant (140 tons). In the second week, the rebar consumption is 39 tons and because there is no rebar delivery, rebar stock level is reduced to 101 tons. The convergence of total rebar cost as the value of objective function in the given generation is shown in Fig. 13. It can be seen that the total rebar cost that has been optimized by GA-MLP algorithm in 200 generations is \$596 128. As indicated in Fig. 13, some discontinuities are common in learning or heuristic process which is not overtrained and consequently overfitted. The only thing that matters is the fact that the general behavior of the graph should be minimized. The amount of error showing the performance of GA-MLP algorithm is presented by Fig. 14. To clarify the concept of error which is measured to present the performance of GA-MLP algorithm, it should be mentioned that, GA chromosomes are actually the coefficients of a polynomial that maximizes our gain in the process of optimization. In other words, it should be defined that in each step forwarding to reach the objective function, how close it has gotten through this function. This process is called minimizing error. Based on this policy we move toward our desired function, the closer we are to the function, the better approximation has been computed by chromosomes. In fact, chromosomes are the coefficients of a polynomial; this polynomial can lead to the answer close to zero, if we substitute it into the objective function. Since GA-MLP is the biased version of the pure GA, we should apply mini-batch inside of the processing algorithm to be able to minimize the error. So, it should be mentioned that on X axis in Fig. 14, the step and mini-batch size is shown, not the epoch or iteration value and Y axis shows the scaled expected error which is the log-likelihood of error so as to visualize the error in a better scale.

To indicate the superiority of the developed GA-MLP algorithm over GA, first the fitness value calculated by GA-MLP is compared to the fitness value calculated by GA illustrated in Fig. 15. The total rebar cost that has been optimized by GA algorithm in 200 generations is \$688 978 which is more than the \$596 128 (the minimum cost obtained from GA-MLP algorithm). Second, the amount of error in both algorithms are compared and presented in Fig. 16. Comparing the error value, it can be concluded that against the error value in GA, the error in GA-MLP algorithm converges toward zero when the mini-batch size is increasing and reaching almost to 600.

Fig. 15. Comparing the convergence of total material cost in 200th generation by GA-MLP algorithm (left) and by GA (right). [Colour online.]

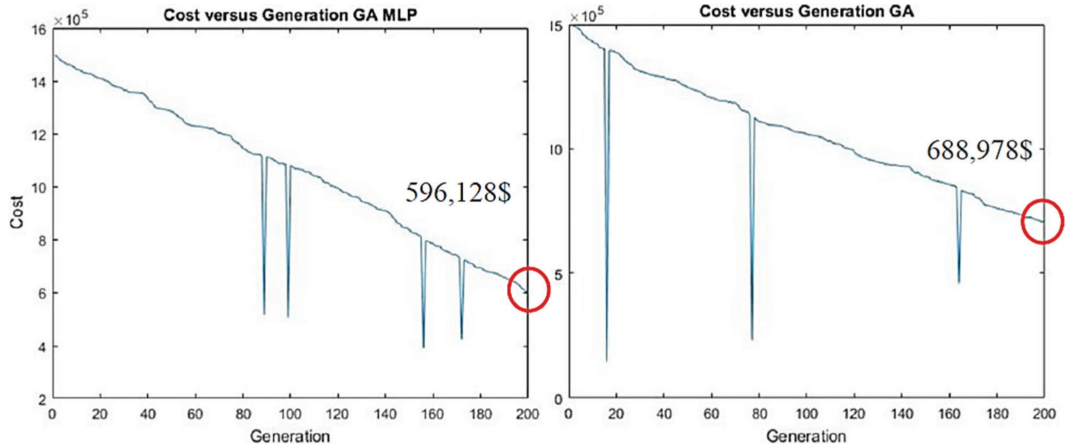
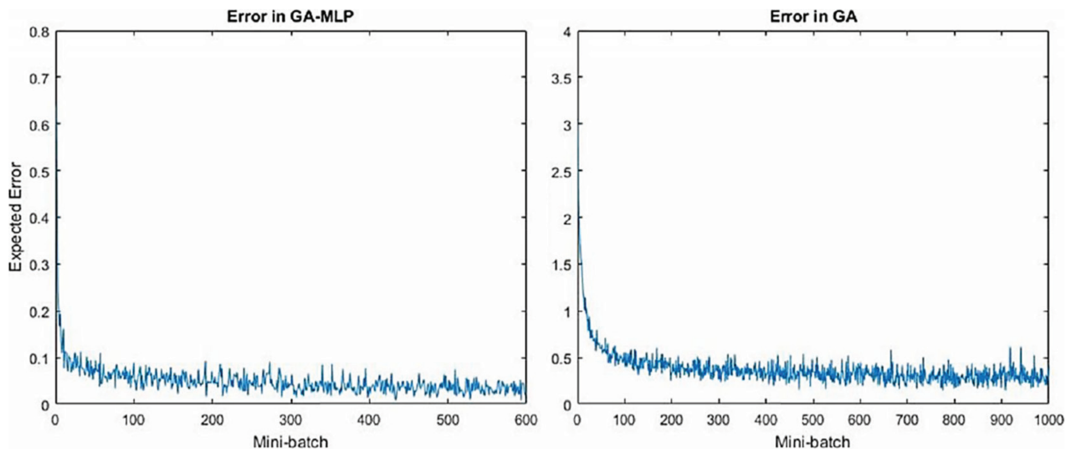


Fig. 16. Comparing error in GA-MLP (left) and error in GA (right). [Colour online.]



Conclusions

The main contribution of this paper lies in the development of a novel automated method as a part of a big material management system (MMS) to generate optimized material delivery schedule that can be used as a guide for contactors or material professionals in procuring material with the least cost and without early, late, excess and insufficient purchasing. The proposed method can make trade-offs and optimize balance among elements of material cost and can also consider the dynamic nature of the construction projects through following up the progress reflected in the last up-to-date schedule. In addition to profiting from the capabilities of GA as a greedy optimization engine, practicality and the excellence of the presented method is due to creating memory for GA by integrating MLP with GA to avoid from getting stuck to the local minima as the main weakness of GA. In fact, MLP gives a capacity of inference to GA by regularizing the parameters using their fluctuation history to be able to jump over the local minima. Moreover, to facilitate the implementation of the automated method computer prototype software has been developed to act as an interface with the user. Validation is done through a numerical example and the outputs in terms of error value and total material cost demonstrate the superiority of GA-MLP over pure GA. In summary, automated GA-MLP method represents a promising way forward to optimize the delivery and inventory of construction materials not only in the planning phase but also in the construction phase.

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