Manageability Challenges for Knowledge Incorporation in Genetic Algorithms: *A Study Using the Meal Planning Problem*

Ngonidzashe Zanamwe[1], Kudakwashe Dube[2], Jasmine S. Thomson[3]
{nbzanamwe@ gmail.com[1], k.dube@massey.ac.nz[2], j.a.thomson@massey.ac.nz[3]}

University of Zimbabwe, Computer Science Department, Number 630 Churchill, Mount Pleasant, Harare, Zimbabwe [1], Massey University, Computer Science & Information Technology Department, School of Engineering & Advanced Technology, PN321, Tennent Drive, Private Bag 11 222, Palmerston North 4442, New Zealand[2], Massey University, Massey Institute of Food Science and Technology, PN321, Massey University, Tennent Drive, Private Bag 11 222, Palmerston North 4442, New Zealand[3]

Abstract. This work investigates manageability challenges for knowledge incorporation in Genetic Algorithms (GAs) for solving the Meal Planning Problem (MPP). The MPP is an intractable problem with optimal solution models in literature leading to solutions that are hard to manage from the knowledge perspective. Manageable incorporation of knowledge into computational models for the MPP will help dietitians in nutrition-based disease therapy administration thereby improving the health of patients. An experimental study implementing a genetic model for the MPP was used to investigate the manageability challenges. The findings were that GAs do not have natural ways of supporting manageable incorporation of knowledge and knowledge incorporated into GAs using existing methods is hard to manage. Manageability is important because knowledge and models become easy to customize to suit different contexts. The novel contribution of this work is a new understanding on the matter of "manageability".

Keywords: knowledge manageability, knowledge manageability challenges, knowledge incorporation into algorithms, Genetic Algorithms, meal planning problem, computational models

1. Introduction

Knowledge incorporation (KI) into Evolutionary Algorithms (EAs) speeds up convergence towards a solution, reduces computational cost and facilitates generation of good solutions [1]. The same is true of KI into Genetic Algorithms (GAs) for solving the MPP since GAs are a class of EAs. In literature, not enough attention has been paid to manageability challenges of KI in algorithms for the MPP. This paper is part of on-going work which seeks to investigate an approach to manageable incorporation of knowledge into solution models for the Meal Planning Problem (MPP) with application in HIV/AIDS nutrition therapy.

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An experimental study implementing a genetic model for MPP was used to investigate the manageability challenges. The GA has been chosen because it is one of the most widely used model for the MPP in literature. The experiment had two parts—the first part (P1) implemented a GA without incorporating much domain knowledge and the second part (P2) implemented the GA with domain knowledge. The GAs were run, meals were produced and evaluated. The novel contribution of this work is a new way of understanding "manageability" and the requirements for manageability of knowledge incorporated into a GA for the MPP.

This paper is organized as follows: Section 2 presents the motivations, context and concepts while section 3 presents related work. Section 4 gives the problem statement and objectives while section 5 presents the manageability framework which is applied in section 6. Section 7 outlines the requirements for manageability and section 8 gives the methodology. Section 9 presents results while section 10 concludes the paper.

2. Motivations, Context and Concepts

This work investigates manageability challenges for KI into GAs for the MPP. This investigation is important for assessing the extent to which knowledge incorporated in a model and the model itself can be customised to suite different contexts with different guideline knowledge. The MPP is a multi-objective and multi-constrained optimisation problem involving designing a set of meals from food ingredients of different nutritional values and volumes. For an elaborate definition of the MPP, see [3]. GAs mimic the natural process of evolution by using techniques inspired by the natural processes of inheritance, mutation, selection, and crossover [19]. A genetic model for the MPP represents candidate solutions as meals which are evolved toward meals that meet nutritional constraints through application of genetic operators (inheritance, mutation, selection, and crossover).

In this work, knowledge is a dimension with four elements [10] presented in Table 1.

Table 1: Knowledge Dimension Elements

Element	Definition	Description
NK	None or no knowledge	No knowledge is incorporated hence solutions are not useful in nutrition therapy administration.
NTK	Non-targeted knowledge	Knowledge not specific to a particular disease/patient is incorporated hence solutions are of limited use to healthy people.
TK	Targeted knowledge	General guidelines about a specific disease/patient are incorporated but are not identifiable and manageable as a complete nutrition therapy guideline. The solutions are only useful to healthy people.
HTK	Highly targeted knowledge	Complete guidelines about a specific disease/patient are incorporated hence solutions are most useful in nutrition therapy administration.

Knowledge incorporated into a GA is manageable if the knowledge is HTK and if operations in Table 2 can be applied to the knowledge and solution.

Table 2: Knowledge Manageability operations

Manageability Operation	Description
Create	Generate a new knowledge base from guidelines
Retrieve/Query	Answer requests for knowledge
Change/update	Modify knowledge base to accommodate changes in guidelines
Delete/Remove	Delete knowledge from the knowledge base
Customise	Modify model and knowledge base to suit specific scenario
Replace	Replace guideline with different one
Share	Export generic version of knowledge base

Meal quality in this paper is measured in terms of the number of nutrients satisfied out of a possible total of 23 nutrients and level of harmony of meal ingredients. The higher both values are, the higher the meal quality. There are three levels of harmony of meal components which are low, medium and high. Low level means that meals are not edible because they contain ingredients with no congruency. Medium level means that meals contain ingredients from correct ingredient categories like breakfast, lunch and dinner but with missing ingredients from other categories. High level means that meals contain ingredients from all ingredient categories and are highly edible.

3. Research Problem and Objectives

This work investigates manageability challenges of KI in a GA for the MPP. The MPP is an intractable problem with optimal solution models in the literature leading to solutions that are hard to manage from the knowledge perspective. Manageable incorporation of knowledge into algorithms for the MPP will help dietitians, clinicians, nutritionists, and caregivers in nutrition-based disease therapy administration, decision making and transfer of knowledge from one region to another thereby improving the health of patients. The objectives of this work were to show that, i) GAs cannot solve the MPP in their natural form without incorporating much knowledge, ii) GAs do not have natural ways of supporting manageable incorporation of knowledge, iii) knowledge incorporated into GAs using existing methods is hard to manage and iv) to engineer requirements for manageable incorporation of knowledge into GAs for the MPP.

4. Related Work: Manageability Challenges in KI Methods

In EAs, KI methods include those that incorporate knowledge in the fitness function, initialisation process and operators [1]. Other methods [2] incorporate knowledge in representation, population initialization, recombination and mutation, selection and reproduction and fitness evaluations. Comparable methods are in [4], [5]. Similarly, [7] proposed knowledge based initialization, crossover mutation, and selection as methods of KI. Existing methods for KI are not manageable because they do not allow for customisation of knowledge and the solution model to suite specialised contexts.

Few works in literature focused on managing knowledge incorporated in computational models. One such work [18] proposed a framework for knowledge management which defined four knowledge manageability operations (create, understand, distribute and reuse). This approach was not manageable because it defined only four operations instead of seven and the knowledge incorporated was not HTK. The field of managing knowledge incorporated in Evolutionary Computational models has not been actively researched in the recent past. However, [20] proposed an approach with only two operations (share and create). Similarly, [13] proposed a Cultural Algorithm in which members of the population acquired, encoded and stored knowledge in a way which allowed knowledge sharing by all members of a population. In addition, [21] proposed a Case-Initialized GA for knowledge extraction and incorporation in which, new knowledge could be created, retrieved and updated. Lastly, [6] proposed an approach to KI into GA which only allowed for creation of knowledge and applying the knowledge-based mutation operator. All these approaches are not manageable because they did not define and apply seven manageability operators and did not incorporate HTK.

5. Framework for Knowledge Manageability Challenges

Fig. 1 shows a new framework for manageability challenges in KI in GAs. The framework has two dimensions-the knowledge dimension (Table 1) and the knowledge manageability operation dimension (Table 2). The knowledge manageability operation dimension shows the number of knowledge manageability operations which can be applied to the knowledge incorporated in a GA. For example, Fig.1 shows that a model has a very very high level of manageability if all the seven operators can be applied to the knowledge and the incorporated knowledge is HTK.

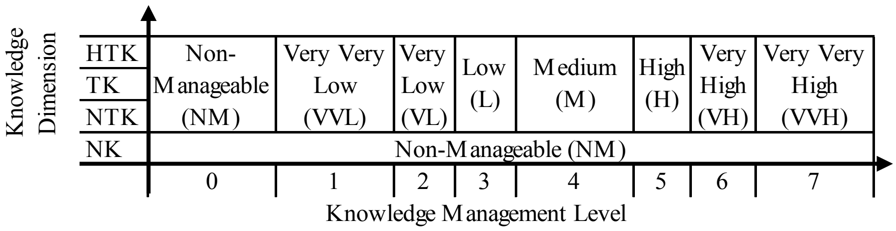

Fig. 1. Framework for Manageability Challenges in Knowledge Incorporation.

This framework defines 8 broad levels of GAs with respect to the knowledge dimension and knowledge manageability operation (MO) dimension. These levels range from non-manageable to very high level in increasing order of knowledge manageability (Fig. 1). NM refers to a class of GAs with no MOs but which can incorporate any knowledge and the GAs are not useful to nutritionists and the knowledge incorporated is very difficult to manage. VVL refers to a class of GAs with 1 out of 7 operations but can incorporate either NTK, TK or HTK and the GAs are not useful to domain experts. VL refers to a class of GAs with 2 out of 7 operations but can incorporate either NTK, TK or HTK. Similar definitions can be given for other classes of GAs which are defined in terms of the number of MOs and knowledge dimension. The last level (VVH) refers to a class of GAs with all 7 MOs and can incorporate either NTK, TK or HTK. The sub-category which incorporate HTK contains GAs that are completely manageable and most useful to domain experts.

6. Application of the Framework for Manageability Challenges

Fig. 2 presents results on the application of the framework in Fig. 1 to works on the MPP modelled using GAs. In Fig. 1, all works except one [17] are using approaches to KI which are not manageable because they did not define any knowledge manageability operator.

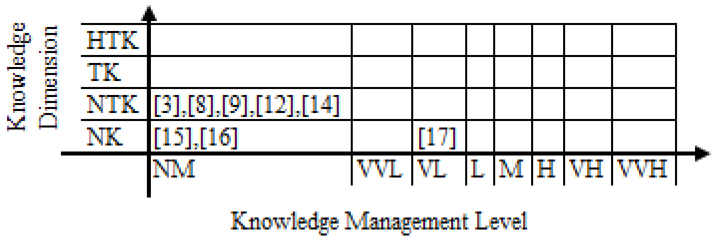

Fig. 2. Evaluation of existing approaches to KI in GA for the MPP

Most of these works fall under the non-manageable class of the framework meaning that approaches to KI used in these works are not manageable and NTK was incorporated in the GA. One work [17] falls in the very low class meaning that the approach to KI used in this work has a very low level of manageability and the work incorporates NTK. Therefore, it can be concluded that, existing approaches do not support manageable incorporation of knowledge into GA for the MPP.

7. Requirements for Manageability of Knowledge in GAs

Fig. 3 presents the requirements for manageability of knowledge incorporated into GA. For knowledge incorporated into a GA to be manageable, the knowledge must be HTK and must be stored in a knowledge base so that the seven manageability operators can be applied to the knowledge. Likewise, the knowledge should then be incorporated into the operators of the GA. When this happens, the genetic operators become knowledge-based for example: knowledge-based population initialization, knowledge based crossover, etc. The framework in Fig. 3 should be knowledge independent that is if the knowledge in the knowledge-base changes, the model must not be affected. For example if the one of the MOs like update is applied, the knowledge based should be modified but not the GA code. Once a knowledge-base for HTK has been developed, the knowledge can be manipulated using the operators and the HTK can then be incorporated into the GA.

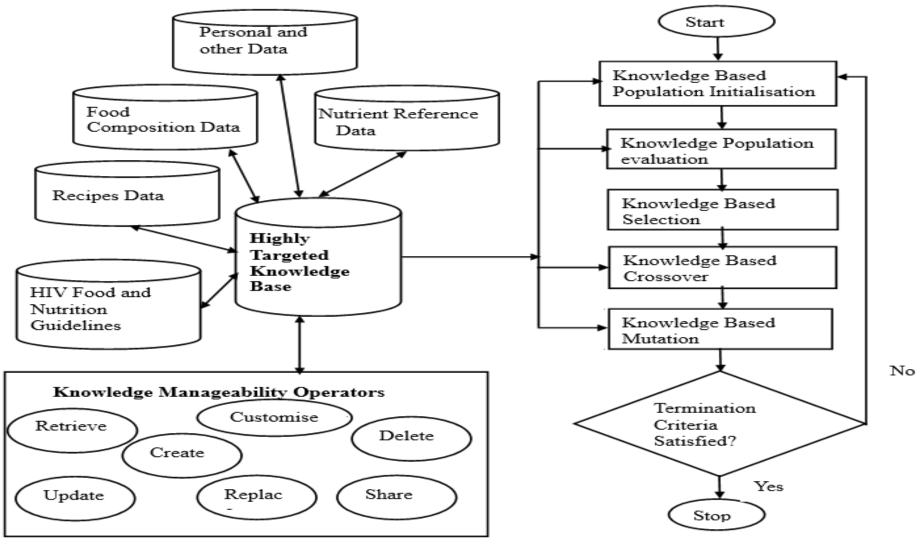

Fig. 3. Framework for Manageable Incorporation of Knowledge into GAs

8. Method for Investigating KI Manageability Challenges in GAs

An experimental approach was used to investigate manageability challenges of KI into the GA. The experiment implemented a GA. The MPP was used as a case study and the experiment had two parts (P1 and P2). P1 sought to show that GAs do not solve the MPP in their natural form without incorporating much knowledge. This was demonstrated by implementing the GA without incorporating much domain knowledge. In P1, personal data and Food Composition Data (FCD) were incorporated in the genetic operators. P2 was aimed at showing that: (1) current KI methods for GA are not manageable; and (2) current GAs do not have natural ways of supporting manageable incorporation of knowledge. In P2, much knowledge (FCD, harmony rules, personal data, food and nutrition guideline knowledge and nutrient reference values) was incorporated in genetic operators and population initialization. P2 had two parts: P21 and P22. Part P21 incorporated the knowledge directly in the genetic operators while in part P22, a Prolog knowledge-base was created and then queried from the GA. Both P21 and P22 incorporated the same knowledge. In this paper P2 refers to both P21 and P22.

Meals from P1 and P2 were compared on quality to further demonstrate that GA do not solve the MPP in their natural form without incorporating much knowledge. The choice of genetic parameters (chromosome length, population size, crossover and mutation probability, etc) was informed by previous studies ([3], [9] and [11]) which implemented GA to solve the MPP. In all experiments, 250 generations were used and the crossover probability was 0.9 while the mutation probability was 0.2. In both P1 and P2, meals were prepared for a male adult aged 35 whose physical level of activity was active and under the assumption that three meals are taken per day.

9. Results and Discussion

Fig. 4 shows the results from both P1 and P2 in which 232 meals were produced for each part of the experiment. Meals from P21 and P22 are just the same hence in Fig. 4 only one line has been plotted for P2.

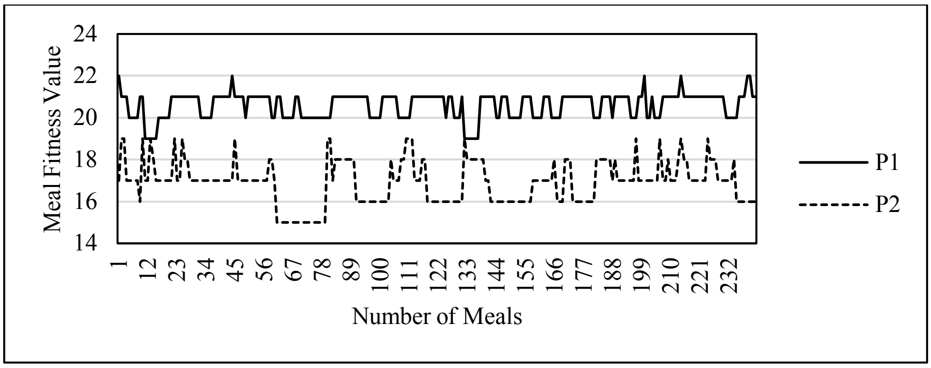

Fig. 4. Sample Meals from the Experiment

Discussion of Results of P1: In P1, little knowledge (personal data and FCD) was incorporated in the GA resulting in meals with high fitness values but low levels of harmony. For example: {Powdered milk-136g, Okra-230g, Cabbage cooked-306g, Turnip-200g, Chicken with skin-428g, Dark bread-162g}. Meals from P1 have higher fitness values because harmony has been sacrificed. Such meals satisfy most nutrient requirements but are not edible.

Discussion of Results from P21: In P21, more knowledge (personal data, FCD, harmony and NRVs) was incorporated in the GA resulting in meals with relatively lower fitness values but higher levels of harmony. For example: {Spinach-486g, Samp-146g, Fish-7g, Lima beans-249g, Mowa-372g, Beans or lentils-79g}. Meals from P1 cannot be classified as either meals for breakfast or lunch or dinner which can be done with meals from P21. In P1, the crossover function does not incorporate knowledge resulting in crossing over of food items which are not in the same category thereby producing meals with very low levels of harmony. The same conclusion can be reached if the other genetic operators are not knowledge-based. In summary, GAs do not solve the MPP in their natural form without incorporating much knowledge. This finding confirms what is in found in literature since there are some works ([8], [3] and [17]) which incorporated domain knowledge in GAs for the MPP even though the knowledge was hard to manage. However, there are very few works in literature which modelled the MPP using GA but without incorporating much domain knowledge and these include [16] and [15]. As can be seen these works are now aged and the current trend is to incorporate domain knowledge in GA in order to solve the MPP.

Discussion of Results from P21 and P22: Knowledge can be incorporated into GAs by either infusing it in the genetic operators or storing it in a knowledge-base queried from a GA. Table 3 shows whether the GA, knowledge and knowledge-base should be changed when the MOs are applied. A tick (✓) in Table 3 means change is necessary for the MO to be applied which a blank cell means no change is required. A question mark (?) means the MO cannot the applied to the GA or knowledge.

Table 3: Changes to be when effected when manageability operations are applied

	Manageability Operation (MO)	**Experiment P_{21}**		**Experiment P_{22}**	
		GA Code Change	*Knowledge Change*	*GA Code Change*	*Knowledge-Base Change*
Standard CRUD Operations on Knowledge	*Create*	✓	✓		✓
	Retrieve/Query				
	Update/Change	✓	✓		✓
	Delete/Remove	✓	✓		✓
Other Domain-Specific Operators on Knowledge	*Customise*	✓	✓		✓
	Replace	✓	✓		✓
	Share	?	?		

As is shown in Table 3, in P21, both the code for the GA and the knowledge had to be changed for knowledge to be created, updated, deleted, customized and replaced. For example, the crossover function was modified such that only food items from the same class could be swapped. This approach to KI is knowledge-dependent meaning that if the knowledge changes, the code also changes. This finding is confirmed by the fact that most works that modelled the MPP using GA incorporated the knowledge in the genetic operators since there is no any other natural way of supporting manageable incorporation of knowledge. The GA does not come with knowledge MOs. Works like [17] devised a way of replacing harmony rules by implementing them as a plug-in. In summary, GA do not have natural (inherent/built-in) ways of supporting manageable incorporation of knowledge.

Discussion of Results from P22: In P22, as is shown in Table 3, no changes are required on the GA code to apply MOs like create, update, delete, customize or replace. Knowledge incorporated this way is very easy to manage and this approach can easily allow for incorporation of HTK. The GA and the knowledge are loosely coupled implying that, if the knowledge changes the GA code is not affected. This is in contrast to works like [8], [3] which attempted to incorporate knowledge into GA but the knowledge was not the HTK and these works and many others in literature did not define the seven knowledge MOs. Here, the more the GA code has to be changed, the harder it is to manage the knowledge. Therefore, knowledge incorporated into GA using existing approaches in literature is hard to manage and hence a new approach has been proposed in which there is GA code and knowledge independence.

10. Conclusion

This work investigated manageability challenges of KI in GAs for the MPP. The major conclusions drawn from this work were, GAs do not solve the MPP in their natural form without incorporating much knowledge, GAs do not have natural ways of supporting manageable incorporation of knowledge and knowledge incorporated into

GA using existing methods is hard to manage. The novel contributions of this work are i) a new understanding on the matter of “manageability” and ii) the requirements for manageability of KI into GAs for the MPP. The significance of this work is that it will help dietitians in food and nutrition-based disease therapy administration, decision making and transfer of knowledge from one region to another thereby improving the health of patients. Future work involves, developing specific techniques for incorporation of HTK knowledge into algorithms used by MPP models; developing a knowledge intensive, generic and manageable model of the MPP; developing strategies for real uses of the model in HIV/AIDS nutrition therapy and application of the model in the mobile web-based context of developing countries to facilitate knowledge transfer.

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