# Molecular Fragments from Incomplete, Real-life NMR Data: Framework for Spectra Analysis with Constraint Solvers

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Abstract: Nuclear Magnetic Resonance (NMR) spectroscopy is a powerful analytical tool that can be used in the elucidation of chemical structures and is widely applied both in academia and industry. Despite using computerassisted structure elucidation systems, interpretation of NMR data is often laborious, requires high levels of expertise and is not immune to ambiguities. In this multi-disciplinary study, we developed a design of a novel system using a Constraint Satisfaction (CS) framework to utilise unannotated NMR spectra. Additionally, our system allows the utilisation of complementary information obtained/known outside the scope of NMR. Herein we describe a prototype implementation and its empirical evaluation on a set of amino acids, which are a diverse class of important biological compounds. We further employ the CS approach to show the principle limits (ambiguity) of the NMR method in molecular structure elucidation.

# **1 INTRODUCTION**

Nuclear Magnetic Resonance (NMR) spectroscopy is a cornerstone analytical method widely used both in academia and industry. One of the main applications of this method is chemical structure elucidation (Elyashberg and Williams, 2015). There are different types of NMR techniques to collect partial structural information on molecular structures of substances under investigation. An example of the type of structural information which can be obtained from NMR spectra is that a molecule should contain a Carbon (C) atom directly bonded to a Hydrogen (H) atom. Various other types of structural information are available from the spectra (Elyashberg and Williams, 2015) which makes it possible to identify/elucidate the structure of the molecule, which constitute the main goal of NMR analysis. The elucidation process is complex, laborious and the results may be ambiguous, so the interpretation of NMR spectra currently requires the involvement of human experts. The research on the automation of the NMR

spectra interpretation and development of Computer-Assisted Structure Elucidation (CASE) systems has been conducted since the 1960s (Koichi et al., 2014) and several such systems are available either as research prototypes or commercial propositions (Burns et al., 2019).

There are still many remaining challenges in computer-assisted NMR analysis: full automation (or greater degree of automation), managing the uncertainty of spectra, handling the ambiguity of the analysis or dealing with the mixtures as opposed to pure substances. The main task of NMR analysis lends itself very naturally to the CS area. Indeed, the partial structural information obtained from NMR spectra can be seen as a set of constraints, with an elucidated molecular structure being a solution to this set of constraints. This observation was a starting point of our investigation and we found it quite surprising that no attempts to apply generic CS techniques (as opposed to specialised algorithms) to NMR analysis have been made until very recently. In (Omrani and Naanaa, 2016; Omrani and Naanaa, 2019) the authors have demonstrated that the basic tasks of NMR analysis can be solved by reformulation of the structural information obtained from NMR spectra as constraints and the application of generic constraint solvers. The open-source system (Omrani and Naanaa, 2019) al-

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lows applying basic types of NMR constraints as well as user-specified allowed/forbidden molecular structures. While this work has demonstrated the viability of the CS-based NMR analysis, important theoretical and practical questions have been left open. First, the power of the proposed method has been illustrated by the case studies but was not systematically assessed. Second, the NMR constraints were considered from the idealised perspective, and no practical limitations of the NMR method were taken into account. For the latter, in the practice of NMR analysis, it is quite common that some theoretically possible NMR constraints are not extractable from the spectra. Furthermore, the ambiguity of the NMR structure elucidation was not addressed.

In this paper, we present the design of the system for NMR interpretation/molecular structure elucidation based on the CS. We take as a principle an inherent incompleteness and uncertainty of NMR derivable partial information about the molecular structures. We consider several classes of constraints, including chemical constraints, such as valency of atoms, NMR constraints such as chemical bond connectivity and other constraints coming either from other types of analysis (e.g. mass spectrometry) or from the practical experience. We discuss the formulation of various types of constraints and report on the experiments with a prototype implementation on the classes of amino acids. We also show that NMR analysis is inherently ambiguous, even when all theoretically possible NMR constraints are available, there are cases when it is still impossible to uniquely identify the molecular structure in question. Thus, we assess the fundamental limitation of the NMR method itself.

### 2 PRELIMINARIES

We will represent the molecular structures as labelled undirected multigraphs, which are formally defined as triples  $\langle V, e, l \rangle$ , where *V* is a set of vertices, *e* :  $V \times V \to \mathbb{Z}^{\geq}$  represents the multiplicity of edges between the vertices, and  $l: V \to A$  labels the vertices by the types of chemical elements. Here *A* is a set of all chemical elements, including e.g. H for hydrogen, C for carbon, etc. We use multigraphs as opposed to graphs to represent faithfully the cases of molecular structures with *multiple* bonds between pairs of atoms. A function  $v: A \to \mathbb{Z}^+$  denotes the valency, fundamental chemical characteristic of the atom types that denotes the maximum capacity of making bonds. For example v(H) = 1 and v(C) = 4.

We will deal in this paper with two main types of 2-D (two-dimensional) NMR spectra used in the elu-

cidation of molecular structures: Heteronuclear Single Quantum Coherence (HSQC) and Heteronuclear Multiple Bond Correlation (HMBC) experiments that correlate signals of <sup>13</sup>C and <sup>1</sup>H atoms. Typically these spectra are visualised as contour plots where the axes coordinates are called chemical shifts with the units of Hertz or the most commonly used normalised scale parts per million (ppm) by convention.

A molecule's structural information appears in the spectra in the form of *peaks* shown as the small spots at the intersection of the chemical shifts of the interacting atoms (see Figure 1 (left) and (right) for peaks in the HSQC and HMBC spectra, respectively). Each peak in the HSQC spectrum corresponds to (or is generated by) a pair of C and H atoms with a *direct* bond between them, meaning the graph-distance between corresponding vertices in the representing multigraph is 1. Similarly, the peaks in the HMBC spectrum identify the pairs of C and H atoms separated by *two* or *three* bonds (i.e distance between corresponding vertices in the multigraph is 2 or 3).

For both types of spectra, x-coordinate, and ycoordinate of a peak represent chemical shifts of corresponding H and C atoms, respectively. The chemical shifts of the atoms persist across different spectra and different atoms may have the same (very close) chemical shifts due to possible symmetries of the molecule. Figure 1 illustrates these principles, where the molecular structure in the middle produces HSQC (left) and HMBC (right) spectra. The (in)equalities of chemical shifts are subject to possible measurement errors and subtle differences in an experimental setup, and they should be considered as approximate. We assume here, as a starting point in constraints formulation, that all necessary approximations/abstractions have been done and it is firmly established which coordinates (shifts) are equal and which are different. This is sufficient to formulate the basic NMR constraints (see Section 3.3). Furthermore, the information about the shifts taking values in a specific range is useful for NMR interpretation and to formulate further NMR constraints (see Section 3.4).

The problem of NMR analysis/interpretation we consider here can be reformulated as *Given a set of NMR-derivable constraints from HSQC and HMBC spectra on the connections between atoms to generate all molecular multigraphs satisfying those constraints*. Additional structural information derived from other NMR experiments can be introduced by extending the constraint set. The ultimate goal of such an analysis is to identify the molecular structures down to the least ambiguous set possible. In the next section, we discuss the important aspects of constraint formulation for this problem.



Figure 1: The connectivity information from HSQC (left panel blue arrow) and HMBC (right panel red arrows) obtained for alanine (middle panel). Additional NMR information such as chemical shifts can be added as optional constraints and are planned to be implemented in the future. NMR Spectra are courtesy of James London.

## 3 CONSTRAINTS FOR NMR ANALYSIS

In the constraint-based NMR analysis, several categories of constraints do naturally occur. Some of them are absolute/rigid, in a sense, they have to be present and satisfied in all reasonable scenarios of analysis, while others are soft constraints that may be present/absent and are not always required to be satisfied. The latter categories reflect inherent incompleteness, uncertainty and practical limitations of the NMR method. Further to that, we consider two different settings for the analysis, in one we seek complete solutions, meaning the full molecular structures, in another, we seek incomplete molecular structures or fragments. The incomplete setting is important, as NMR-derivable information is often insufficient to recover the full molecular structure and other sources of information are needed, but the recovered fragments may be still useful for NMR spectra interpretation. Yet another aspect of NMR interpretation is whether an analysis of pure substances or mixtures is required. All these variants of the problem affect the ways some constraints are formulated. In this section we discuss the constraints in an implementationindependent form; the details of the implementation of a prototype system can be found in Section 4.

## 3.1 Molecular Graph Representation Constraints

The solutions of NMR CS are thought in terms of labelled undirected multigraphs, so the following rigid constraints are necessary:

- $e(x,y) \ge 0$  (**M**)*ultigraph*;
- e(x,y) = e(y,x) (U)*ndirected*;

• e(x,x) = 0 (N)*o* Loops;

Due to the *additivity* of NMR spectra when applied to *mixtures* as opposed to *pure substances*, NMR derived constraints are related to all participating molecules. In the case of the analysis of *pure* substances as opposed to the *mixtures*, the solutions need to represent a single molecule, so the connectedness constraint is required:

• the molecular multigraph is connected (C)onnectedness

Notice that to consider the case of mixtures with unknown numbers of components it is sufficient just to omit  $\mathbf{C}$  constraint - the disconnected multigraphs solutions will then include representations of the molecular structures of the components. Due to the complexity of the connectedness constraint, we propose to treat it at the post-processing stage, that is not to include it as a constraint, generate all solutions and then filter them on connectedness condition.

#### **3.2 Basic Chemistry Constraints**

All molecular structures are constrained by the valency, the fundamental chemical property of the constituting atoms. This imposes the following constraints depending on the settings:

- $\forall x \in V \ d(x) = v(l(x))$  (complete setting) (VC)
- $\forall x \in V \ d(x) \le v(l(x))$  (incomplete setting) (VI)

Here d(x) is a degree of a vertex x in a multigraph, that is  $\sum_{y \in V} e(x, y)$ , v is a (predefined) valency function, and l is a atom type labelling function.

### 3.3 NMR Constraints

It is significant to express the HSQC and HMBC spectra clearly in terms of constraints. The HSQC experiment identifies a single bond between the pairs of C and H atoms and the HMBC spectroscopy detects correlated atoms separated by two or three bonds in the multigraphs. Let the HSQC and HMBC spectra contain the peaks  $p_{i,j}$  with  $1 \le i \le t_1$ ;  $1 \le j \le t_2$  and  $q_{k,m}$ with  $1 \le k \le s_1$ ;  $1 \le m \le s_2$ , respectively. Let the coordinates (chemical shifts) of these peaks be  $(h_i, c_j)$ and  $(h_k, c_m)$ , respectively. We will use the following useful abbreviations:

 $dist^{(1)}(x, y)$  for e(x, y) > 0 (The HSQC peaks),

 $dist^{(2)}(x,y)$  for  $\exists z \ (e(x,z) > 0 \land e(z,y) > 0)$ , and  $dist^{(3)}(x,y)$  for  $\exists z, v \ (e(x,z) > 0 \land e(z,v) > 0 \land e(v,y) > 0)$  (The HMBC peaks).

Then basic NMR constraints are defined as:

•  $\exists \bar{x} \exists \bar{y} (HSQC(\bar{x}, \bar{y}) \land HMBC(\bar{x}, \bar{y}) \land ID(\bar{x}, \bar{y}))$ (NMR)

where:

- $\bar{x} = x_1, \dots, x_m$  and  $\bar{y} = y_1, \dots, y_n$  are sequences of variables
- $HSQC(\bar{x},\bar{y})$  is  $\bigwedge_{i,j}(dist^{(1)}(x_{h_i},y_{c_j}) \wedge l(x_{h_i}) = H \wedge l(y_{c_j}) = C)$
- $HMBC(\bar{x}, \bar{y})$  is  $\bigwedge_{k,m}((dist^{(2)}(x_{h_k}, y_{c_m}) \lor dist^{(3)}(x_{h_k}, y_{c_m})) \land l(x_{h_k}) = H \land l(y_{c_m}) = C)$
- $ID(\bar{x}, \bar{y})$  is  $\bigwedge_{c_i \neq c_j} (x_{c_i} \neq x_{c_j}) \land \bigwedge_{h_i \neq h_j} (y_{h_i} \neq y_{h_j})$

Thus, the basic NMR constraints assert the existence of pairs of C-H atoms satisfying necessary distance conditions, imposed by HSQC and HMBC spectra ( $HSQC(\bar{x},\bar{y})$ ,  $HMBC(\bar{x},\bar{y})$ , respectively), as well as by identity conditions ( $ID(\bar{x},\bar{y})$ ). Notice that in the case when some peak coordinates are equal (within one spectrum or across both), e.g.  $c_i = c_j$  then corresponding variables  $y_{c_i}, y_{c_j}$  are the same.

### 3.4 Further Constraints

#### 3.4.1 Exact/Partial Formula Constraints

Due to the partiality of NMR-derived information, any additional information can be very useful for structure elucidation. Other forms of analysis, including different variants of spectroscopy (e.g. Mass-Spectroscopy (MS)), may provide partial or full information on a Molecular Formula (MF), that is the count of different types of atoms involved in the molecule. Thus, for any known count n of a type of atom T involved in a molecule adds a formula constraint:

• 
$$|\{x \mid l(x) = T\}| = n$$
 (F)



Figure 2: The workflow of the system. Demonstrating how the system works for different data inputs.

#### 3.4.2 Optional Constraints

It is not uncommon to have prior information on expected or impossible fragments during structure elucidation and use it as optional constraints. This information can be derived either from the knowledge of the work being done or from the NMR data itself. For example, if the analysed mixture is obtained through a chemical synthesis all the precursor materials used, the by-products and the products are known. If no cyclic structures (e.g phenyl rings) are present, this information can be imposed as an optional constraint to prohibit cyclic solutions. Similarly, any expected fragments can also be forced to the solution space.

### 3.5 Post-processing

In the proposed design, we assume that some of the constraints may be computationally expensive to deal with by a generic constraint solving or depending on the solver, may be infeasible to express in its input language. In such cases, the constraints can be used for filtering the solutions at the post-processing stage. In the implemented prototype we experimented with the connectedness constraint being used for filtering at the post-processing stage. Furthermore, post-processing can be used to further reduce the number of solutions by removing equivalent multigraphs. In this vein, we experimented with partial/full isomorphism checks and filtering of obtained multigraphs.

# 4 PROPOSED FRAMEWORK AND PROTOTYPE IMPLEMENTATION

The proposed high-level design of the constraintbased NMR interpretation system from the discussed principles is presented in Figure 2. The system supports different sources of the input data - it may come either as pre-processed experimental spectra (lists of peaks/chemical shifts) or as ideal constraints generated from known molecular structures data (molecular files). The latter is used for the testing and the investigation of inherent ambiguity related to the CS approach for NMR data analysis. Once all constraints are formulated, based on the input data, a generic constraint solver is applied which results in the set of all possible molecular structures (labelled multigraphs) satisfying the constraints. Post-processing (e.g. connectedness, or isomorphism filtering) is applied after that, and if the results remain ambiguous/inconclusive, the set of constraints can be updated and processing repeated.

The current prototype system is implemented in Python and constraints programming platform Numberjack (Hebrard et al., 2010), and its constraint solver Mistral (Hebrard, 2008) is used. The opensource RDKit software (Landrum, 2016) is used to handle the connection between atoms and draw molecular structures. To identify isomorphic structures and to enumerate all nonisomorphic ones, we used a standalone Nauty tool, which relies on canonical labelling algorithms (McKay and Piperno, 2014). In this work we have used Nauty to check isomorphism of labelled graphs.

The performance of the system has been tested by using known structures of chemical compounds. Therefore, the NMR data for simple amino acids are chosen from the Biological Magnetic Resonance Data Bank (BMRB) website to be the data set for the system (Ulrich et al., 2007).

## 5 EXPERIMENTS, RESULTS AND EVALUATION

All the experiments were implemented on Intel Core CPU's with frequency 2.20 GHz running Ubuntu 18.04.5 and using 7 GB of RAM.

To test our approach we generated full sets of HSQC and HMBC constraints for all 20 amino acids from their chemical structures and calculated incomplete solutions and part of complete solutions (Table 1 and 2, respectively). In each case, the solu-

tions were subsequently filtered at the post-processing stage to find all connected and nonisomorphic multigraphs. In Table 1, C and H atoms were considered in the incomplete setting experiment. For 18 out of 20 amino acids, we reported the number of all possible solutions with time in seconds and the number of nonisomorphic structures with the time taken to filter the solutions in seconds. For two amino acids, we stated an 'out of memory' case while running the system. To tackle this case, we might need further optimisation for the current implementation, including using different constraint solvers. Multiple solutions were generated by the constraint solver for amino acids, with the number of solutions increasing significantly with the increased complexity of the molecular structure, represented by the number of atoms in a Molecular Formula (MF). Much higher number of solutions was generated when the MF was used as additional source of constraints (complete solutions), compared to the incomplete solution set. Isomorphic filtering only partially reduced the number of solutions, demonstrating intrinsic ambiguity of the constraint sets.

Inspection of the partial solutions for alanine in Figure 3 reveals several reasons for multiple solutions. Most of the solutions are linear structures where the C atom that does not have H atom attached (no corresponding HSQC peak) is positioned either at the end of the chain or between the two atoms that have H atoms. This type of ambiguity is caused by the intrinsic ambiguity of HMBC constraints that correspond to either two or three-bond separation between the interacting atoms. This ambiguity can be resolved by introducing additional NMR connectivity constraints.

The second source of ambiguity is uncertainty in the number of H atoms attached to each C. Since C has

Table 1: Incomplete solutions calculated for amino acids using only NMR data as the input.

Amino acid	MF	Structures							
		# Sols	Time (s)	Nonisomorphic	Time (s)				
Alanine	$C_3H_7NO_2$	25	0.00	15	0.00				
Arginine	$C_6H_{14}N_4O_2$	1952	0.32	716	0.00				
Asparagine	$C_4H_8N_2O_3$	104	0.00	60	0.00				
Aspartic acid	$C_4H_7NO_4$	104	0.00	60	0.00				
Cysteine	$C_3H_7NO_2S$	25	0.00	15	0.00				
Glutamine	$C_5H_{10}N_2O_3$	456	0.04	172	0.00				
Glutamic acid	$C_5H_9NO_4$	456	0.04	172	0.00				
Glycine	$C_2H_5NO_2$	3	0.00	3	0.00				
Histidine	$C_6H_9N_3O_2$	6204	0.81	2060	0.02				
Isoleucine	$C_6H_{13}NO_2$	1977	0.33	427	0.01				
Leucine	$C_6H_{13}NO_2$	2279	0.33	346	0.01				
Lysine	$C_6H_{14}N_2O_2$	2555	0.42	676	0.01				
Methionine	$C_5H_{11}NO_2S$	910	0.11	163	0.00				
Phenylalanine	$C_9H_{11}NO_2$	136221	35.85	30735	0.69				
Proline	$C_5H_9NO_2$	603	0.12	85	0.00				
Serine	$C_3H_7NO_3$	25	0.00	15	0.00				
Threonine	$C_4H_9NO_3$	142	0.01	39	0.00				
Tryptophan	$C_{11}H_{12}N_2O_2$	out of memory	-	-	-				
Tyrosine	$C_9H_{11}NO_3$	out of memory	-	-	-				
Valine	$C_5H_{11}NO_2$	603	0.14	85	0.00				

a valency of four, a terminal C can have up to three H atoms attached, and C in the middle of the linear chain can have maximum two H atoms. The number of H atoms can be determined in the multiplicity-edited HSQC experiment. The number of possible variants caused by these two ambiguities increase dramatically with the number of C atoms in the molecule, as clearly seen from Table 1 and 2.

The third type of ambiguity is caused by the possibility to form cyclic compounds. Only single cycle variant is possible with three C atoms, but in more complex molecules the number of cycles can increase significantly. Small cycles of three and four atoms are chemically unstable, which justifies using additional constraint that eliminate small cycles. Constraints on the number of H atoms attached to C may automatically eliminate cycles through the valency constraints.

Including the MF to generate complete solutions increase the ambiguity for amino acids further (Table 2) because it introduced N and O atoms not detected in the NMR experiments. As the result, only valency constraints can be formulated for these atoms, allowing them to take any position in the molecule. However, for molecules that only contain C and H atoms the MF constraints maybe highly beneficial because they would eliminate structures with the incorrect total number of H atoms.

Our analysis highlights intrinsic ambiguity of the NMR data and critical contributions from additional constraints for unambiguous determination of the molecular structure. In the majority of CASE systems, including the CS system of (Omrani and Naanaa, 2016) the MF is required, and these constraints are rigidly embedded into the system; very often the software would not run if these parameters are not defined. This limits the usability of the systems, as most of the time only partial information on these parameters is available at best. It may also lead to incomplete or incorrect results, as possible solution are not explored systematically. In contrast, our system explicitly defines all constraints used in finding the solution and allows to explore the constraints systematically. The system can be used with any set of constraints, often incomplete, which allows its application at all stages of the NMR analysis. The inspection of the results, as outlined above, can suggest further experiments to eliminate ambiguities, until a unique solution is found.

From a more theoretical perspective, we propose to consider the obtained results in the complete setting (including the formula) as evidence of the limits of the NMR method itself. Indeed, in a considered variant of NMR analysis including HSQC and HMBC spectra, even in the presence of all theoret-

Table 2: Complete solutions calculated for amino acids us-	-
ing NMR data and the MF as the inputs.	

Amino acid	MF	Structures				
		# Sols	Time (s)	Nonisomorphic	Time (s)	
Alanine	$C_3H_7NO_2$	662	0.10	148	0.00	
Cysteine	$C_3H_7NO_2S$	8081	1.51	779	0.01	
Glycine	$C_2H_5NO_2$	78	0.00	34	0.00	
Leucine	$C_6H_{13}NO_2$	4091	2.41	136	0.00	
Proline	$C_5H_9NO_2$	15066	3.69	764	0.03	
Serine	$C_3H_7NO_3$	8081	1.51	783	0.01	
Threonine	$C_4H_9NO_3$	24153	5.81	732	0.04	
Valine	$C_5H_{11}NO_2$	2654	0.81	64	0.00	

ically possible ideal NMR constraints (derived from the known structure) the target structure can not be identified uniquely. The numbers produced measure an inherent ambiguity of the NMR method. We suspect that it remains the case even in the presence of further realistic constraints. The proposed CS-based approach addresses such questions systematically and this is a subject of our ongoing and future work.

#### 6 RELATED WORK

The current study contributes to the existing knowledge by addressing several structure elucidation problems. Unlike similar existing constrained structures generating systems, the paper suggests an analytical approach that considers being as realistic and practical as possible. As a result, the program generates all possible structures based on real-world constraints, considering the minimum available information.

There are a set of limitations that may affect the molecular structure elucidation results. One potential drawback that might be encountered is the uncertainty of NMR data, caused by the different environments, especially during the acquisition of NMR data, for solvent or temperature, which can create significant noise of the spectra data. Further improvements should be taken into account to tackle these problems. In the literature, several approaches have been proposed to develop CASE systems over the past century. The Dendral project (Smith et al., 1981), is a pioneer in structure elucidation systems based on NMR spectra. The main aim of the Dendral group was to develop computer systems to assist the chemists in identifying unknown chemical structures (Gray, 1988). The project's main achievement was to introduce the CASE systems' idea to elucidate the chemical structure. There has been a significant increase in publications that document other CASE systems' approaches due to the development of NMR techniques. The examples of these CASE systems are SENECA platform-independent package (Steinbeck, 2001), MONOREG (Ferreira et al.,



Figure 3: Solution multigraphs built from chemical and NMR constraints derived from alanine data. 15 multigraphs satisfied the constraints and were connected and nonisomorphic. The box labelled (Solution 11) is the correct structure. The structure at the bottom right is the complete structure of alanine and the highlighted parts in red corresponds to Solution 11.

2001), Bruker CMC-se program (Kessler and Godejohann, 2018), Logic for Structure Determination (LSD) (Plainchont et al., 2013), Advanced Chemistry Development (ACD)/ Structure Elucidator Suite (Elyashberg et al., 2002), Mestrelab MNova structure (Burns et al., 2019) and MOLGEN 5.0 (Gugisch et al., 2015). The majority of these approaches rely on complex sets of rules defined by experts, and specialised algorithms, which limits their effectiveness and adaptation for complex systems, such as molecular mixtures. The constraint-based systems, we argue for in this paper, separate rules (constraints) formulation and constraint solving, which make them much more flexible and adaptable. Such systems allow utilising the performance of generic constraint solvers. According to (Omrani and Naanaa, 2016), the framework of CS provides an effective solution to structure elucidation problems. A program was developed to generate molecular structures based on satisfying several predefined constraints. The first constraint is the MF. In addition, the number of bonds for each atom and the type of bonds are given as inputs to their system. The system can also impose substructures to appear in the results and forbid specific fragments to exist in the generated structures. The authors have published a recent study describing a new open-source system CP-MolGen (Omrani and Naanaa, 2019).

However, from a practical perspective, the amount of minimum required information to use the framework proposed by the authors is challenging to obtain and even unfeasible in some cases. The MFs are not always readily available. Determining the number of bonds may require extensive analytical data from different instruments. A detailed map of specific distance between atoms is a complicated process that usually is incomplete. For example, HMBC experiments are used to map out the bond distances but HMBC experiments cannot distinguish between two or three bonds (Janovick et al., 2020). This information needs to be inferred from other data available similar to a CS approach. In practice, after obtaining such detailed data elucidating the molecular structure is a trivial process and using a constraint solver is generally not necessary.

Structure elucidation can be formulated as a more generalised CS problem, and approximate solutions can be proposed with a more realistic amount and type of input information. All constraints can be formulated exactly and explicitly, which allows avoiding biased solutions. Such a CS approach to obtain a list of approximations down to the least ambiguous set would be more useful in practical applications. Such a list of solutions can even indicate which experiments to perform next to get a unique solution. In a typical NMR analysis, samples usually consist of chemical mixtures or contain contaminants that have signals indistinguishable from the compounds of interest.

Thus, the amount of experimental NMR information is very limited, which leads to incomplete connectivity and a lack of separation of the observed signals into groups corresponding to different molecules. Sometimes partial information on the MFs can be obtained from the MS analysis, but cannot be related to the NMR signals. These challenges are impossible to address with the reported CS implementation of (Omrani and Naanaa, 2016). The CASE system we have presented addresses this particular need and allows obtaining a full list of possible chemical structures irrespective of the completeness of the NMR information. This creates a powerful computational tool for NMR data analysis and guidance for the selection of additional experiments to establish an objectively unique solution.

## 7 CONCLUSIONS

This paper presents a method of interpreting NMR spectra data via the CS framework to generate molecular multigraphs. Real-world chemical structures instances demonstrate that obtaining constraints based on NMR data is successfully predicts the correct molecular multigraphs. While alternative CS methods exist, which can determine the correct structures for the molecules based on several defined constraints, the interpretation of spectra data in our approach has the advantage of generating the structures based on the minimum available information as the case of the real practical NMR instances. Although we solve the structures predicting problems, we did not consider more complex natural compounds. For instance, chemical structures containing ring compounds and the existence of symmetry for some atoms of the structures. The main challenge would be that it can not easily differentiate between the atoms as two or more atoms will be had the same values of chemical shifts. Further measures are suggested to improve the performance and to predict robust and confident structures. The actions should define the most appropriate methods to handle any uncertainty of NMR data as this is more likely to be encountered in real instances of spectra data.

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